

EXHIBIT 4

Expert Report of Katie Mendoza
November 18, 2024

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EXPERIENCE

I am a research specialist with over 18 years of experience applying advanced statistical modeling, hydrologic analysis, and climate science to environmental challenges. My work primarily focuses on improving water resources, environmental sustainability, and understanding the impacts of climate variability. I develop data-driven solutions that help inform policy decisions, guide resource management, and support the sustainability of natural systems.

Since 2020, I have worked as a Research Specialist III at Texas A&M AgriLife Research, where I lead the development and calibration of hydrologic models, including the Soil and Water Assessment Tool (SWAT). In this role, I conduct comprehensive hydrologic analyses, adapting mathematical and statistical models to evaluate surface and groundwater data, analyzing datasets to provide insights on water quality, availability, and management. I work closely with government agencies including the US Environmental Protection Agency (USEPA) and the US Army Corps of Engineers (USACE) to deliver solutions that inform water quality regulations, resource planning, and environmental policy decisions. My contributions have directly supported federal and state agencies in developing strategies for more sustainable land and water use.

Throughout my career, I have applied my background in statistical theory and mathematical modeling to a wide range of environmental research. From 2006 to 2021, I worked as a Research Associate at the Center for Research on the Changing Earth System (CRCES) where I spent 15 years investigating the impacts of decadal climate variability on water resources and agriculture. There, I also used the SWAT model to develop statistical models to forecast droughts, floods, and other climatic phenomena, helping to predict their effects on water systems, crop yields, and barge transportation in the Mississippi and Missouri River Basins.

I regularly present research findings at national and international conferences and have co-authored multiple peer-reviewed publications, including seven specifically pertaining to the SWAT model.

My academic background in meteorology, with a Bachelor's and Master's degree from Florida State University in 2004 and 2006, respectively, has provided me with a foundation in both theoretical and applied atmospheric science.

A copy of my CV is attached to this Report.

COMPENSATION AND TESTIMONY

I have been retained by the State of Oklahoma at a rate of \$175 per hour. My compensation does not depend on the outcome of the trial/hearing in this case and has not influenced my opinions outlined in this Report. I have not testified at trial or by deposition in the past four years.

ASSIGNMENT

I was tasked with using the Illinois River Basin (IRB) SWAT model I created, calibrated, and analyzed to answer the following questions about the Illinois River Watershed (IRW) in Oklahoma:

1. What can the SWAT model tell us about trends in the phosphorus loading and phosphorus concentrations occurring in the rivers and streams of the Illinois River Watershed in Oklahoma since 2010?
2. What can the SWAT model tell us about whether phosphorus from poultry waste land application – both historic and current – is a significant contributor to current phosphorus loading in the rivers and streams of the Illinois River Watershed in Oklahoma?

3. Approximately what percent of the phosphorus loading through the rivers and streams into Lake Tenkiller is coming from point sources and what percent is coming from nonpoint sources?
4. Assuming all land application of poultry waste in the IRW ceased in 2010, would legacy phosphorus from pre-2010 poultry waste land applications still be a substantial contributor to phosphorus loading in the IRW in the future?
5. Using the SWAT model, and assuming a cessation of poultry waste land application practices in the Illinois River Watershed (but no other changes) in 2010, would phosphorus from historic poultry waste land application continue to contribute to exceedances of the .037 water quality standard in the rivers and streams of the Illinois River Watershed in Oklahoma?
6. What can the SWAT model tell us about whether there exist land management techniques that could help reduce phosphorus loading from historic and current poultry waste land application practices in the Illinois River Watershed?
7. Using the SWAT model, what effects on phosphorus loading / phosphorus concentrations would these various land management techniques have?
8. Do you have any critiques of the Arkansas SWAT model, and if so, what are they?

SUMMARY OF OPINIONS

Below is a summary of my opinions for each of the eight questions listed above. I hold the opinions expressed in this report to a reasonable degree of scientific certainty based on my professional experience, training, education, and available data and information. The methods used in this report and my analysis are reliable, widely accepted within the industry, verifiable, and supported by peer-reviewed publications. The basis of these opinions is described in detail in the report that follows.

1. Daily phosphorus concentration averaged yearly from 2010-2020 shows an increase in trend along tributaries and main channel of the Illinois river leading into Lake Tenkiller. The concentration of total phosphorus across the entire watershed, over the entire time of simulation is well above the scenic water quality standard of 0.037 mg/l for the state of Oklahoma. The land with poultry houses, where poultry waste land application is simulated, is contributing to the headwaters of the river and streams and accumulating as they flow downstream ending up in Lake Tenkiller.
2. Both historic and current poultry waste land application are significant contributors to the current phosphorus loading. 20% of the total phosphorus from the poultry waste applied in the watershed remains in the soil year after year. The model shows the historic (legacy phosphorus) contribution from the soil has an average annual increase of 57% of phosphorus loading in the river and streams coming from the amount of phosphorus in the soil.
3. There is approximately 3.46% of the total phosphorus loading through river and streams into Lake Tenkiller coming from point sources and 96.54% coming from nonpoint sources.
4. Legacy phosphorus will still be a substantial contributor to phosphorus loading in the IRB in the future. Total phosphorus in the soil has two components, organic phosphorus and soluble phosphorus. Soluble phosphorus is equivalent to the soil test phosphorus (STP) field measurements. So, soluble phosphorus is the critical component of total phosphorus when looking at overall soil health. Even though there was a decrease in total phosphorus in the soil during the 21-year simulation, the watershed average of soluble

phosphorus in the soil increased ~0.8 lbs/ac and organic phosphorus in the soil decreased ~2.5 lbs/ac. So, the decrease in the soil is driven by the decrease in organic phosphorus. Organic phosphorus in the soil is decreased when it is converted into soluble phosphorus, and organic phosphorus can also attach to sediment and be removed from the soil. Starting the model in 2010 and simulating a cessation of poultry waste land application shows the soluble phosphorus is no longer drastically increasing year after year. However, there still is an increase in soluble phosphorus year over year.

5. If there was a cessation of poultry waste land application in the IRB in 2010, the historic application of poultry waste would still be a significant contributor to the exceedance of the 0.037mg/l water quality standard in the rivers and streams in the IRW in Oklahoma. The total phosphorus concentrations in the last year of the 21 year simulation of no poultry waste application starting in 2010, range from 0.032 mg/l in subbasin 45 in OK, to 0.62 mg/l in subbasin 11 in AR, with the total phosphorus concentration at the outlet of the watershed at Lake Tenkiller of 0.24 mg/l, and an overall watershed annual average concentration of 0.22 mg/l, which is ~600% over the standard.
6. When simulating no additional poultry waste land application starting in 2020, the overall loading of total phosphorus into the rivers and reaching Lake Tenkiller will reduce on average 5.6% a year. If 4% of the over grazed pastures have no additional poultry waste application and are used for hay production, this decrease is 9.6% annually on average. When 15m (~49 foot) filter strips are applied on all pasture land coupled with the cessation of poultry waste land application, then the loading into the rivers and lake has an average annual decrease of 62%. In order to reduce the amount of loading that reaches the rivers and Lake Tenkiller, additional management practices are needed beyond the cessation of poultry waste land application.
7. When simulating no additional poultry waste land application starting in 2020, the overall concentration of total phosphorus in the river reaching Lake Tenkiller will reduce in concentration by 0.017 mg/l or ~90,100 lbs. When an additional land management technique of adding a ~49 foot (15 meter) filter strip on the edge of all pasture fields across the entire watershed, the model simulates an average reduction of 0.2 mg/l or ~1,000,000 lbs. Simulation of hay production from the 4% of land that previously had poultry waste applied and was over grazed, results in a 0.03 mg/l or ~154,361 lbs average annual reduction. This shows that simply ceasing poultry waste application is not sufficient to reduce the concentration of total phosphorus in the river.
8. I have several critiques of the Arkansas SWAT model (UIRW model), including input data used and methods used for calibration. Some of the most troubling issues with the UIRW model include:
 - The UIRW model simulated 417,600 lbs of phosphorus loading which is not consistent with what has been reported in the NPDES since 2007.
 - The UIRW model input soluble phosphorus values into the soil based off Storm et al 2006 values from early 1990s (1991-1995), but it used a value of 0.01 for organic phosphorus and didn't put in any initial values for nitrogen. Not accurately initializing the soil with both components of phosphorus and nitrogen can cause discrepancies and uncertainty in the model.
 - There were differences in land use classification. The UIRW model grouped land use into three classes- Forest, Hay, and Urban. The IRB model used 22 unique land use classifications.
 - The UIRW model applied poultry waste at rates ranging from 0.03 to 1.9 ton/acre. The Oklahoma Conservation Commission (OCC) stated that most machinery used to apply poultry waste cannot apply at rates less than 0.5 ton/acre. The nutrient content of the UIRW model poultry waste was much higher than the IRB model and speciated differently.
 - The UIRW model estimated the removal of 814,631 tons of poultry waste per year. OCC stated removing this much poultry waste from the watershed is unrealistic.

- The UIRW model simulated a manure rate of 40 lbs/ac/day, which would require cattle to eat more than 60-70 lbs/day, so the pasture would need to produce ~20 tons of grass to support cattle, which is not possible.

METHODOLOGY

SWAT MODEL

Texas A&M AgriLife Research, United States Department of Agriculture-Agricultural Research Service (USDA-ARS), and USDA- Natural Resources Conservation Service (NRCS) scientists, working collaboratively in Temple, Texas, have a long (40+ years) history of developing, implementing, and supporting the use of hydrologic, water quality, soil quality, and plant growth models to improve management of agricultural and rural lands. The centerpiece of that cooperation has been the Soil and Water Assessment Tool (SWAT), [Neitsch et al, 2009; Arnold et al, 2013] developed by USDA-ARS scientists in close collaboration with Texas A&M AgriLife Research scientists. It is the world's most widely used, tested, and verified small watershed-to-river basin-scale model that simulates surface and groundwater quality and quantity, soil moisture, and vegetation growth. More than 7,000 peer-reviewed publications¹ are published worldwide for numerous applications from more than 90 countries. In addition, more than 50 active researchers are involved in continuing the development of the SWAT model to keep it at the cutting edge of research. All the models and tools developed are open-source and public domain, allowing input and contributions from all users worldwide to the continued development of the model and associated tools.

Over the last decade, this cooperation has extended to numerous organizations that have used the SWAT model for strategic planning and decision-making related to soil, water, and crop management. These collaborators have included the US Agency for International Development (USAID), USACE, Department of Energy (DOE), National Oceanic and Atmospheric Administration (NOAA), US Geological Survey (USGS), National Aeronautics and Space Administration (NASA), USDA-ARS, Bureau of Reclamation (BOR), The Nature Conservancy (TNC), many related universities and State and local water resources and environmental agencies in the US, and several agricultural and environmental agencies and universities worldwide.

HAWQS

More recently, Texas A&M AgriLife Research scientists have worked with U.S. Environmental Protection Agency (USEPA) to develop a user-friendly platform², the Hydrologic and Water Quality System (HAWQS) [HAWQS 2.0, 2023], for a seamless application of SWAT anywhere in the contiguous United States. HAWQS incorporates SWAT and all input databases and user interfaces to simulate any watershed/river basin in the contiguous United States. The SWAT projects in HAWQS have been calibrated for hydrology and selected quality parameters throughout the United States and are routinely used by USEPA and several state environmental agencies and universities. Texas A&M AgriLife Research has also assisted several countries (India, Nigeria, South Africa, Brazil, and others) and states to develop customized versions of HAWQS for their specific needs.

¹ <https://swat.tamu.edu/publications>

² Hydrologic and Water Quality System (HAWQS), Quality Assurance Product Plan, US EPA Office of Water (April 1, 2014): Texas A&M AgriLife Research Contract with USEPA re: HAWQS: *Contract No: C_DOCCM130105CT0027 EP-G11H-00057 and*

"Environmental analysis and evaluation using HAWQS" Ecosystem Processes Division Landscape and Aquatic Systems Modeling Branch Quality Assurance Project Plan US EPA, Office of Research and Development, Center for Environmental Measurement and Modeling, (Jan. 22, 2024); Contract No: 68HE0C18D0001

The HAWQS platform was used by the USEPA for initial model setup for the Waters of the United States (WOTUS) rulemaking³ and is actively using the HAWQS regional model capabilities for modeling for the Meat and Poultry Products Effluent Guidelines upcoming rulemaking⁴. The HAWQS platform was also used by the USEPA Office of Research and Development (ORD) to evaluate the sensitivity of riparian buffer designs on nutrients and sediment loadings into the watershed scale streams⁵ (Ghimire et al., 2021; 2022).

OK-HAWQS is a state specific HAWQS platform developed for the Oklahoma Water Resources Center and the Oklahoma Conservation Commission (OCC) to use the SWAT model to model watersheds across the state including watersheds draining into OK from neighboring states. The OK-HAWQS platform allows for transparent assessing of the watershed for load allocation and implementation of mitigation measures to improve the water quality. In addition to Total Maximum Daily Load (TMDL) development, the tool is used to characterize watersheds in OK and help assess and maintain the land through conservation and proper management. In Oklahoma many waterbodies are impaired according to 303d listings, and the OK-HAWQS provides a common platform in assessing water quality and watershed management to remedy the impaired watersheds across the state. The IRW is an example of an impaired watershed in need of a model to help assess the sources of water quality impairment. Impaired waterbodies from 2022 were compiled from both the state of OK⁶ and AR⁷ to create Figure A. The IRB SWAT model was created through the OK-HAWQS platform for the OCC to help develop TMDLs and a watershed management plan for the impaired waterways in the IRW. The IRB model covers everything in the IRW that drains into Lake Tenkiller.

The HAWQS and OK-HAWQS platforms were not developed for purposes independent of this litigation.

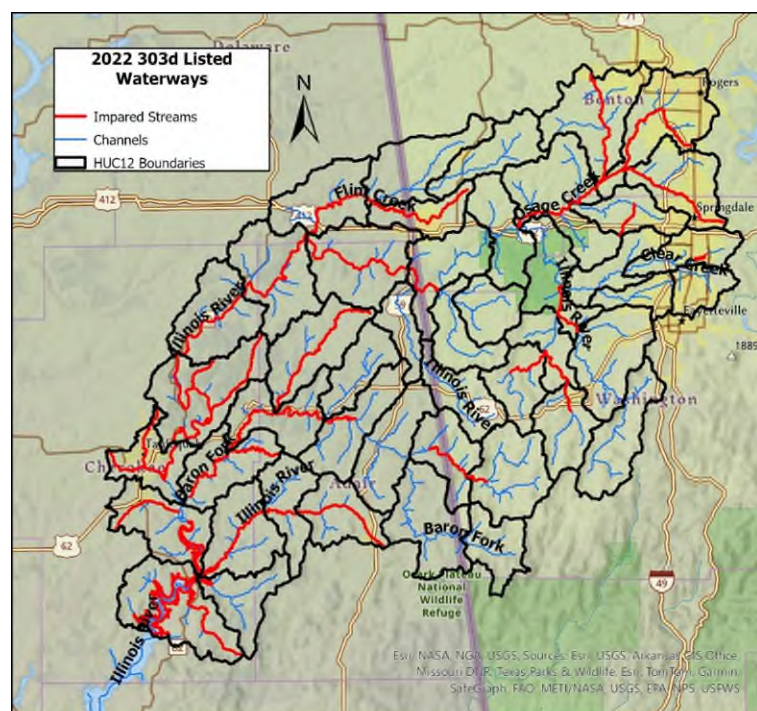


Figure A. Waterways in the Illinois River Watershed that are listed on the 303d list in 2022.

³ <https://www.federalregister.gov/documents/2023/01/18/2022-28595/revised-definition-of-waters-of-the-united-states>

⁴ <https://www.epa.gov/eg/meat-and-poultry-products-effluent-guidelines#current-rulemaking>

⁵ U.S. Environmental Protection Agency Office of Research and Development Center for Environmental Measurement and Modeling (CEMM), Ecosystem Processes Division (EPD) Landscape and Aquatic Systems Modeling Branch (LASMB) Quality Assurance Project Plan Title: Sensitivity of Riparian Buffer Designs on Nutrients and Sediment Loadings into the Watershed Scale Streams

⁶ https://www.deq.ok.gov/wp-content/uploads/water-division/OK_2022-Appendix-C-Final.pdf

⁷ <https://www.adeq.state.ar.us/water/planning/integrated/303d/pdfs/2022/2022-draft-impaired-waters.pdf>

WATERSHED DATA

HAWQS provides federally generated and approved pre-assembled data necessary to specify SWAT watershed models for any study area within the conterminous United States. All data included has undergone rigorous quality control and quality assurance.

Table 1 summarizes the data source(s) for each input dataset. The complete technical documentation detailing the process of data processing for each dataset can be found on the HAWQS platform under the documents and support page.⁸ Using these federally approved and quality assured datasets as input into the model results in an accurate representation of the watershed, therefore the outputs of the model can be allocated to the different land use types and management practices.

Table 1: Summary of data sources used to generate HAWQS 2.0 input datasets.

Input Dataset	Source	Specifications
Weather	PRISM	1981 – 2020 (gridded)
Soil	USDA National Resources Conservation Service (NRCS) Soil Survey Geographic (SSURGO) Database	2018
	USDA NRCS State Soil Geographic (STATSGO) Database	2018
Land Use	National Land Cover Database (NLCD)	2016
	USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL)	2014 – 2017
	USDA NASS Fields	2006 – 2010
	U.S. Fish and Wildlife Service (FWI) National Wetlands Inventory (NWI)	2018
Aerial Deposition	National Atmospheric Deposition Program (NADP)	1980 – 2020 (monthly)
Watershed Boundaries	EPA NHDPlus v2	2019
Stream Networks	EPA NHDPlus v2	2019
Elevation	USGS National Elevation Dataset (NED)	2018 (10-meter DEM)
Point Sources	EPA Hypoxia Task Force (HTF)	2019
	EPA Integrated Compliance Information System National Pollutant Discharge Elimination System (ICIS-NPDES)	2019
Management Data	USDA NRCS crop management zone data	2010
Ponds, Potholes, and Reservoirs	U.S. Army Corps of Engineers (USACE) National Inventory of Dams (NID)	2018
	EPA NHDPlus v2	2019
Crop Data	USDA NASS CDL	2014 – 2017
Wetlands	FWS NWI	2018
Water Use	USGS Water Use in the United States	2015

⁸ https://hawqs.tamu.edu/content/docs/HAWQS_2.0_Technical_Documentation.pdf

ILLINOIS RIVER BASIN MODEL SET-UP

Using the HAWQS (2023) platform, an IRB model was created at the HUC12 scale using the subbasin 111101030906 (Lake Tenkiller) as the outlet. This resulted in a model with 46 subbasins and 6,906 hydrologic response units (HRUs)- areas with unique land uses, soils, and slopes- covering a total area of 3,976.24 km² (~982,500 acres). 99.86% of the HRUs in the watershed were modeled with a slope less than 2%. Only a very small portion of the HRUs in the watershed had slopes >2%. There was no HRU aggregation done for the IRB model to ensure when updating the model with current management practices across the basin, that every unique combination of land use type, soil, and slope would be available to receive area specific management practices.

The location of each land use type is shown in Figure 1 and the amount of area and percent of the watershed covered is found in Table 2. The HAWQS generated model included 25 ponds and 42 Integrated Compliance Information System National Pollutant Discharge Elimination System (ICIS-NPDES)⁹ permitted point sources across the watershed as shown in Figure 2. A complete list of the permitted point sources and corresponding HUC12 and subbasin IDs are shown in Table 3.

The model uses constant daily values calculated from the ICIS-NPDES permitted point sources. This can cause some deviations from the point source loading for any given year in the simulation. Point source discharge can be impacted by the amount of rain. Therefore, in years with above average rain, the simulated point source loading might be under simulated, and in years with below average rain, the point source loading could be under simulated. This may contribute to some of the uncertainty in the total phosphorus calibration. However, using constant values for point source loading is a valid, universally accepted, method to use in the SWAT model given the uncertainty in the reporting of the ICIS-NPDES data.

Pond locations in the model were found using the NHDPlus v2 waterbodies dataset. Any waterbody located within the watershed with storage of less than 25,000 acre-feet were classified and modeled as ponds. The function of these ponds is to protect big water supply reservoirs by storing the sediments and nutrients generated across the watershed locally. They were built in 1930-50s with federal funds on private lands.¹⁰

Table 2. Land use area and percentage of watershed.

Land Use	Area (acres)	% of Total Area
PAST	427,417	43.53
FRSD	414,868	42.25
FRST	38,973	3.97
URLD	32,022	3.26
URMD	17,549	1.79
RNGB	11,481	1.17
RIWF	11,080	1.13
RNGE	10,364	1.06
URHD	6,687	0.68
FRSE	6,546	0.67
WATR	1,376	0.14
BARR	899	0.09

⁹ <https://echo.epa.gov/tools/data-downloads/icis-npdes-download-summary>

¹⁰ <https://www.nrcs.usda.gov/conservation-basics/conservation-by-state/north-dakota/small-watershed-program-pl556>

FESC	803	0.08
SOYB	652	0.07
RIWN	588	0.06
UPWN	272	0.03
UPWF	203	0.02
WWHT	76.6	0.008
URTR	47.0	0.005
COWW	27.2	0.003
ALFA	17.3	0.002
RYE	12.4	0.001

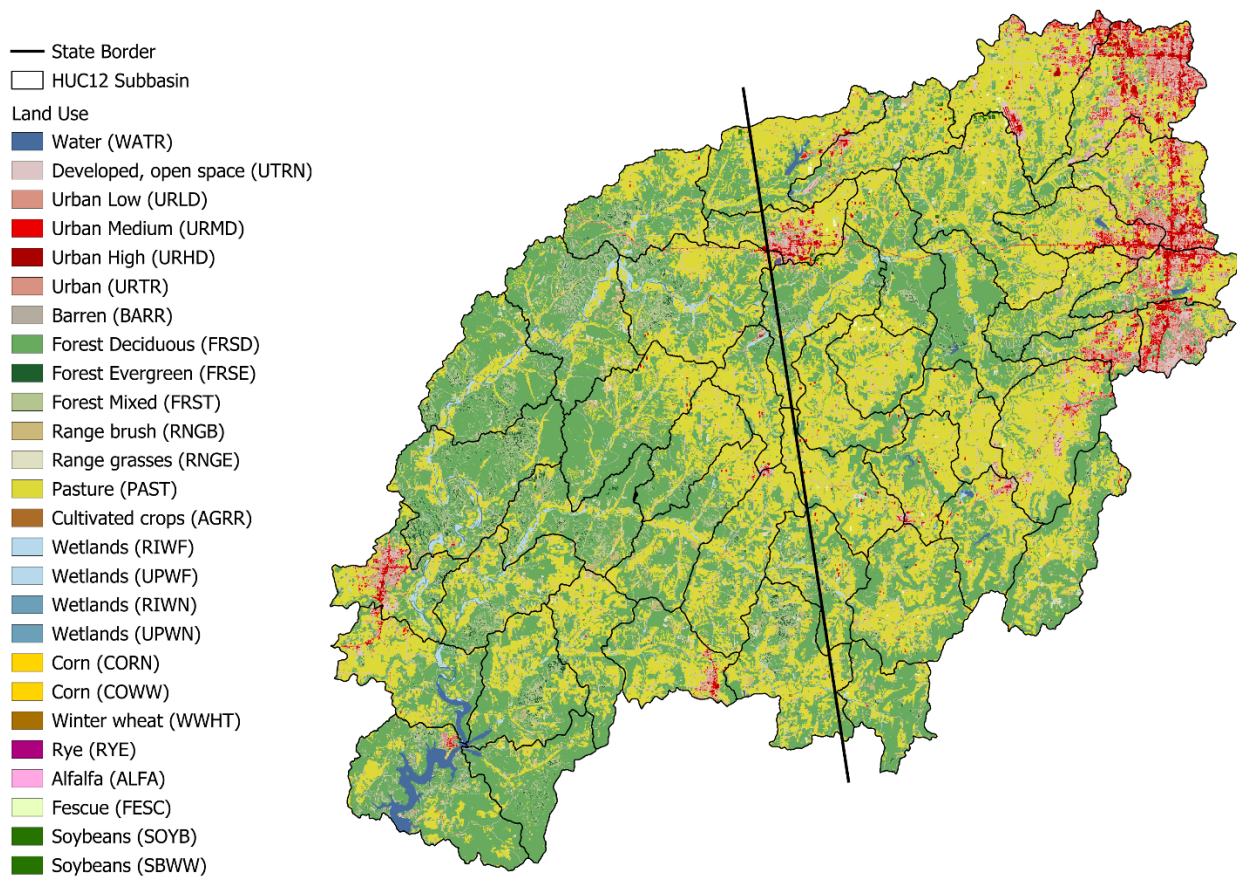


Figure 1. Land use across the IRB watershed.

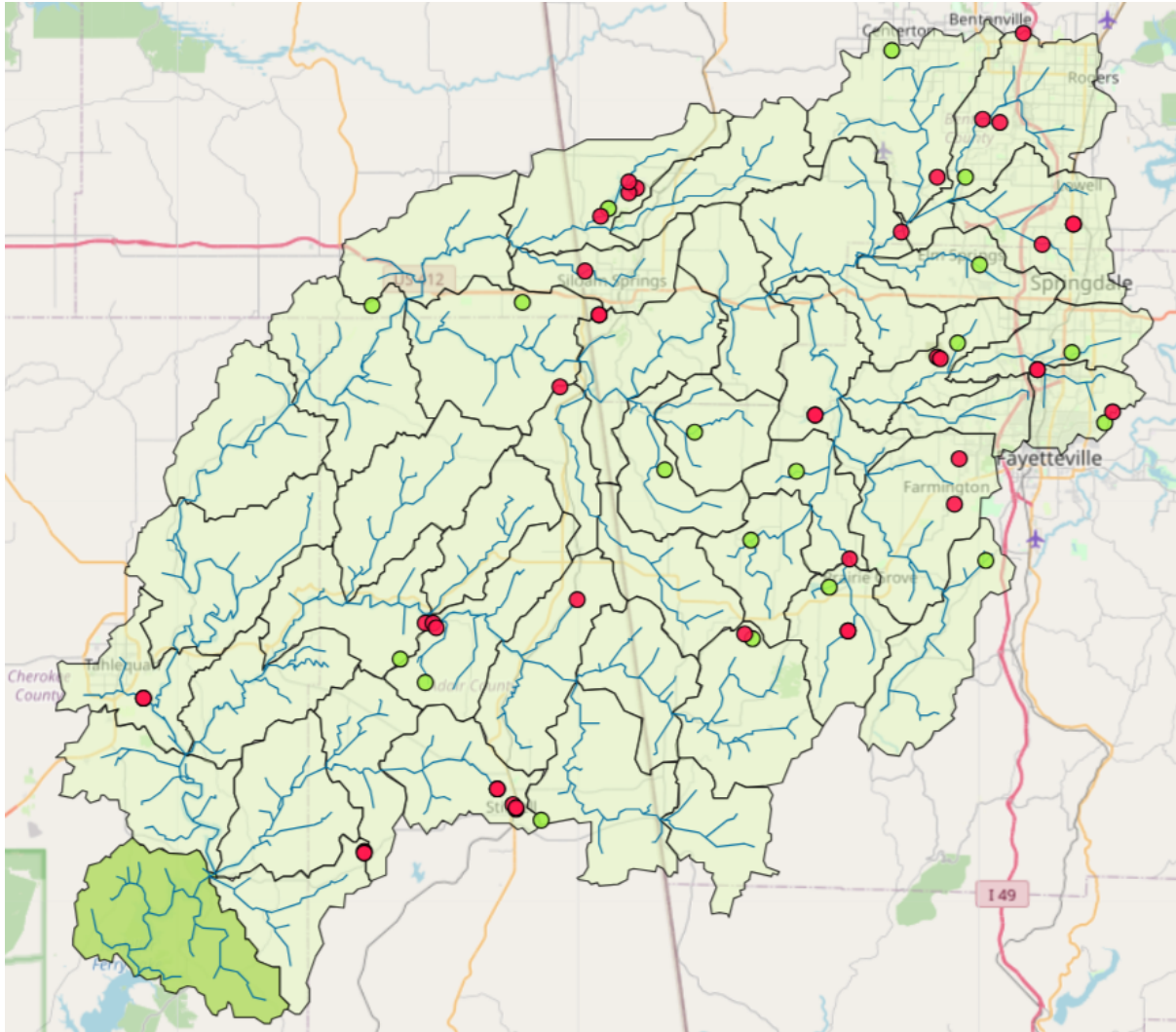


Figure 2. The Illinois River Basin watershed model with HUC12 subbasins. The green circles represent ponds, and the red circles represent permitted NPDES point source outfalls.

Table 3. Permitted point sources across the IRB watershed.

NPDES_ID	Outfall_ID	Subbasin (huc12)	Sub. ID	NPDES_ID	Outfall_ID	Subbasin (huc12)	Sub. ID
AR0050288	001-A	111101030102	2	AR0020184	001-A	111101030503	18
ARG550569	001-S	111101030102	2	AR0037842	401-A	111101030503	18
AR0033910	001-A	111101030103	3	AR0037842	001-A	111101030503	18
AR0033910	001-Q	111101030103	3	AR0037842	101-A	111101030503	18
ARG250008	001B-A	111101030201	4	ARG640175	101-A	111101030606	25
ARG250008	001A-A	111101030201	4	ARG640175	101-Q	111101030606	25
ARG550636	001-S	111101030202	5	AR0035246	001-A	111101030701	27
ARG160045	003-A	111101030204	7	OKP003073	001-A	111101030605	24
ARG160045	001-A	111101030204	7	OK0028126	001-A	111101030705	31
AR0043397	001-B	111101030301	8	OK0045586	003-A	111101030707	33
AR0043397	002-A	111101030301	8	OK0045586	002-A	111101030707	33
AR0050652	001-A	111101030301	8	OK0045586	004-A	111101030709	35
AR0022063	001-A	111101030302	9	OK0026964	TX1-Q	111101030804	40
ARG750087	001-A	111101030302	9	OK0026964	001-A	111101030804	40
ARG750087	001-Q	111101030302	9	OK0030341	001-A	111101030901	41
AR0052868	001-A	111101030303	10	OK0030341	TX1-Q	111101030901	41
AR0050024	001-A	111101030305	12	OKG830049	001-A	111101030901	41
AR0022098	002-A	111101030401	13	OKP003044	001-A	111101030901	41
ARG640066	101-A	111101030401	13	OKP003044	002-A	111101030901	41
ARG640066	101-Q	111101030401	13	OKG950050	001-A	111101030905	45
AR0020273	001-A	111101030502	17	OKG950050	002-A	111101030905	45

After the IRB model was created, a baseline scenario was created. This scenario was created using the PRISM¹¹ (Parameter-elevation Relationships on Independent Slopes Model) weather data, and the simulation was set to run from 1/1/1998 to 12/31/2020 using a 2-year warm-up period. Monthly output was selected for printing, and the latest version of the Soil & Water Assessment Tool (SWAT)¹² model, rev 688, was selected. Under the “Customized SWAT Inputs” section of the HAWQS platform, no additional modifications were made; however, verification that the model did not receive any previous calibration parameter values was ensured. The model was then run within the HAWQS platform resulting in a baseline -- non-calibrated -- HUC12 model simulation of the IRB watershed. This project was then zipped and downloaded to modify and calibrate offline.

OBSERVATIONAL DATA

Streamflow

The first step for flow calibration was to retrieve the USGS gages flow data for calibration to encompass both Arkansas (AR) and Oklahoma (OK) regions within the watershed. Table 4 summarizes the 12 locations and time period used for flow calibration across the IRB watershed. Figure 3 shows the locations of each of the USGS gages used for calibration. Daily flow observations were obtained for each USGS gage and the monthly average flow was used for flow calibration. At any location where the drainage area ratio was larger than 10% (see Table 5 for values) between the USGS gage drainage area and the cumulative area of the subbasin for the gage location, the observational data was multiplied by the ratio to provide an equivalent comparison to the simulation.

¹¹ <https://prism.oregonstate.edu/>

¹² <https://swat.tamu.edu/>

Table 4. USGS gages and the observational time period used for flow calibration.

	Sub.	USGS Gage ID	Gage Name	Lat.	Long.	Calibration Period
AR	3	07194800	Illinois River at Savoy, AR	36.103	-94.344	10/2000-2/2020
	8	07195000	Osage Creek near Elm Springs, AR	36.222	-94.288	1/2000-12/2020
	16	07195800	Flint Creek at Springtown, AR	36.256	-94.434	1/2000-12/2020
	25	07195430	Illinois River South of Siloam Springs, AR	36.109	-94.533	1/2000-12/2020
	27	07196900	Baron Fork at Dutch Mills, AR	35.88	-94.486	1/2000-12/2020
OK	17	07195865	Sager Creek near West Siloam Springs, OK	36.202	-94.605	1/2000-12/2020
	19	07196000	Flint Creek near Kansas, OK	36.186	-94.707	1/2000-12/2020
	25	07195500	Illinois River near Watts, OK	36.13	-94.572	1/2000-12/2020
	35	07197000	Baron Fork at Eldon, OK	35.921	-94.839	1/2000-12/2020
	37	07196090	Illinois River at Chewey, OK	36.104	-94.827	1/2000-12/2020
	39	07196500	Illinois River near Tahlequah, OK	35.923	-94.924	1/2000-12/2020
	43	07197360	Caney Creek near Barber, OK	35.785	-94.856	1/2000-12/2020

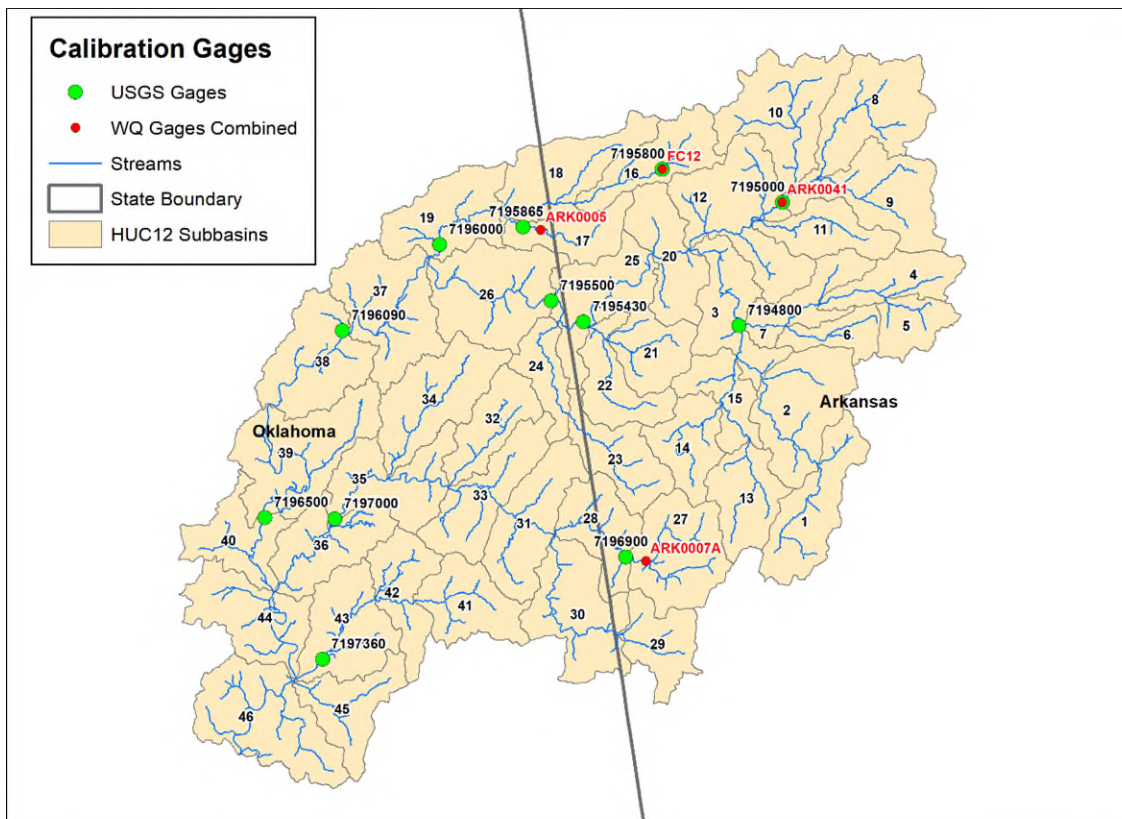


Figure 3. Locations of all gages used for both flow and water quality calibration across the IRB.

Water Quality

For the WQ calibration, all available data from the USGS gages were obtained over the same time period as the flow used 1/2000 – 12/2020. Variables of interest for calibration were total nitrogen (TN), Nitrate (NO_x), total phosphorus (TP), Orthophosphate (OP), and suspended sediment concentration (SSC). In addition to the USGS gage data, local data was obtained from the Arkansas Water Resources Center (AWRC) and the Arkansas Division of Environmental Quality (DEQ). The WQ data obtained were from grab samples for each location taken at various days and times throughout the time period. To calibrate WQ data, it first needs to be interpolated into a continuous time series using continuous flow data and a statistical tool, which is described in detail below. Since most of the local data grab samples were not on the same stream as, or close to a continuous flow gage, only four local stations were used for WQ calibration.

The first three AR stations used were from the DEQ. Station ARK0041 was combined with USGS gage 07195000, station ARK0007A was combined with USGS gage 07196900, and station ARK0005 was combined with USGS gage 07195865. Figure 4 shows the agreement between the combined observations of total phosphorus for one combination of gages, the other two also have good agreement between the period of observation and the concentration amount.

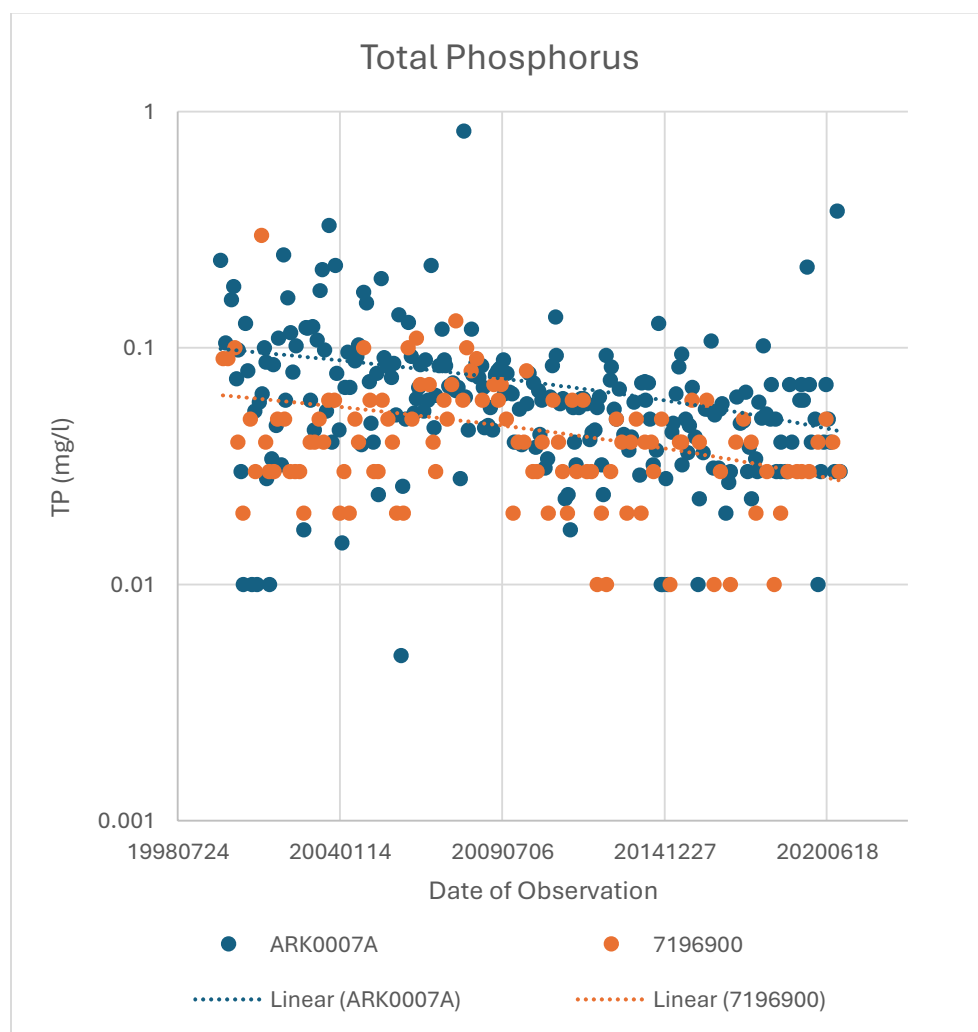


Figure 4. Total Phosphorus (TP) concentration of grab samples from USGS gage 07196900 and station ARK0007A.

The fourth AR station used for WQ calibration was on Flint Creek at Springtown, AR, station FC12 from AWRC. This station was in the same location as USGS gage 07195800. The USGS gage did not have WQ observations, therefore only WQ observations from FC12 were used in the calibration for that location.

All locations used for WQ calibration are shown in Figure 3 and summarized in Table 5 including period of calibration and WQ constituents used at each location. Additionally, to accurately compare observations to simulated values, a method commonly used to compare drainage area and flow called the ratio of the drainage area method¹³ was used. The drainage area ratio was calculated for each USGS gage using the drainage area and the cumulative area of the subbasin containing the gage. The observational flow was adjusted for any location where the area ratio was greater than 10% before the WQ data was converted into a continuous time series using LOADEST.

Table 5. Locations, time period, and constituents used to include the area adjustment ratio used for water quality calibration.

	Subbasin	USGS Gage/Combined	area diff	WQ Time Period	WQ Constituents
AR	3	07194800	1.57	10/2001-12/2020	NO _x , OP, TP, SSC, TN
	8	07195000-ARK0041	1.00	01/2000-12/2020	TP, SSC, TN
	16	07195800 (FC12)	2.06	07/2009-06/2015	TP, SSC, TN
	25	07195430	1.10	01/2000-12/2020	NO _x , OP, TP, SSC, TN
	27	07196900-ARK0007A	1.01	01/2000-12/2020	TP, SSC, TN
OK	17	07195865-ARK0005	1.14	01/2000-12/2020	TP, SSC, TN
	19	07196000	1.09	01/2000-12/2020	NO _x , OP, TP, SSC, TN
	25	07195500	1.00	01/2000-12/2020	TP, SSC, TN
	35	07197000	1.00	01/2000-12/2020	NO _x , OP, TP, SSC, TN
	37	07196090	1.04	06/2010-12/2020	NO _x , OP, TP, SSC, TN
	39	07196500	1.00	01/2000-12/2020	NO _x , OP, TP, SSC, TN
	43	07197360*	1.05	01/2000-09/2010	NO _x , OP, TP, SSC, TN

*SSC is from 2/2001-8/2010

LOADEST

The USGS LOADEST (Load Estimator) tool is a powerful and widely used software developed by the United States Geological Survey (USGS) to estimate the transport of sediment and nutrients in rivers and streams. LOADEST utilizes three statistical models to estimate the loads of sediment, nutrients, and other contaminants based on available WQ data. The Adjusted Maximum Likelihood Estimation (AMLE) and Maximum Likelihood Estimation (MLE) are appropriate when the calibration model errors (residuals) are normally distributed, and the Absolute Deviation (LAD) is an alternative when the residuals are not normally distributed.

For the IRB, the AMLE statistical model was used to generate the constituent load used for calibration. Time series of streamflow, dates and time of observations, and constituent concentration were input into LOADEST. The resulting estimation of constituent load was generated including the mean load estimates, standard errors, and 95 percent confidence intervals on a monthly timestep.

¹³ <https://pubs.er.usgs.gov/publication/sir20065286>

The summary statistics used to determine if the estimated load should be used for calibration were the Load Bias in Percent (B_p), where positive (negative) values indicate over (under) estimation. The model should not be used when the + or - bias exceeds 25%. The Partial Concentration Ratio (PCR) is another measure to show the amount of over or under estimation and is calculated using B_p .

$$PCR = (B_p + 100) / 100$$

PCR values > 1 indicate overestimation; values < 1 indicate underestimation. Finally, the Nash Sutcliffe Efficiency Index (E) (Nash and Sutcliffe, 1970). values range from -infinity to 1.0 with $E = 1$ a perfect fit to observed data, $E = 0$ the model estimates are as accurate as the mean of observed data, and $E < 0$; the observed mean is a better estimate than the model estimates. Table 6 shows the resulting LOADEST summary statistics for total phosphorus for each location across the IRB.

Table 6. LOADEST summary statistics for water quality across the IRB.

TP				
Station	State	B_p [%]	PCR	E
07194800	AR	-7.21	0.928	0.47
07195000-ARK0041	AR	-6.58	0.934	0.44
FC12 (07195800)	AR	-11.51	0.885	0.55
07195430	AR	3.23	1.032	0.42
07196900-ARK0007A	AR	-0.58	0.994	0.30
07195865-ARK0005	OK	1.75	1.017	0.45
07196000	OK	-0.03	1	0.61
07195500	OK	2.95	1.03	0.43
07197000	OK	3.66	1.037	0.28
07196090	OK	2.32	1.023	0.59
07196500	OK	7.94	1.079	0.37
07197360	OK	-1.39	0.986	0.64

CALIBRATION

The IRB watershed SWAT model utilized all the available observed flow data in the study period (2000–2020) for the calibration considering the findings of Shen et al. (2022) and Arsenaault et al. (2018) and skipped the validation step. While conducting model calibration-validation studies over 463 watersheds across the United States using 50 different data splitting schemes, Shen et al. (2022) found that model calibration using full available data and skipping model validation entirely is more robust than the traditional split-sample methods. They found that split sampling requires the modeler to make subjective decisions without clear guidelines, and that calibrating a model on older data then validating the model on new data produces inferior model testing period of performance and should be avoided. Similarly, Arsenaault et al. (2018) highlighted robustness of calibration on full time series over split-sample methods. They concluded that including all years of data available for calibration then using that same period to simulate the scenarios is the most robust way to conduct calibration. This is the approach that was used in calibrating the IRB SWAT model.

Model Performance Metrics

Next the simulated flow was compared with the observational flow to see if the default parameters simulated flow acceptably. The performance metrics used when comparing the SWAT simulation to the observed data for both the verification and re-calibration are the Nash-Sutcliffe efficiency (NSE), Percent BIAS (PBIAS), and Kling-Gupta efficiency (KGE). From the EPA approved QAPP that was used to develop HAWQS, both NSE and PBIAS performance metrics were used to evaluate calibration of the models. The QAPP¹⁴ stated the same acceptable criteria for the NSE and PBIAS as outlined below and used in the IRB model. For the IRB model, but all three metrics are reported.

Nash-Sutcliffe efficiency (NSE)

The NSE is a normalized statistic that determines the relative magnitude of the residual variance (“noise”) compared to the measured data variance (“information”) (Nash and Sutcliffe, 1970). NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. The value of NSE ranges from $-\infty$ to 1 where the value near 1 refers to a good fit of the model and values <0.0 indicate that the mean observed value is a better predictor than the simulated value, thereby demonstrating unacceptable model performance. The value for NSE is calculated by:

$$NSE = 1 - \frac{\sum_{i=1}^N (O_i - S_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2}$$

where O_i is the observed value, S_i is the simulated value, \bar{O} is average of observed values, and N is the total number of observations.

Good performance is indicated by values >0.5 and acceptable performance by values between 0.0 and 0.5 (Moriassi et al., 2007). More specifically, $NSE > 0.75$ is considered very good, NSE between 0.6 to 0.75 is considered good and NSE between 0.4 to 0.6 is considered satisfactory. This is applicable to flow, sediments, and nutrients.

Percent bias (PBIAS)

PBIAS measures the average tendency of the simulated data to be larger or smaller than their observed counterparts (Moriassi et al., 2007). The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values of PBIAS indicate model underestimation bias, and negative values indicate model overestimation bias. PBIAS is calculated by:

$$PBIAS = 100 \left(\frac{\sum_{i=1}^N (S_i - O_i)}{\sum_{i=1}^N O_i} \right)$$

Where O_i is the observed value, S_i is the simulated value and N is the total number of observations.

Table 7 provides the range of acceptable values for PBIAS for flow, sediment, and nutrients consistent with current best modeling practices.

¹⁴ Hydrologic and Water Quality System (HAWQS), Quality Assurance Product Plan, US EPA Office of Water (April 1, 2014): Texas A&M AgriLife Research Contract with USEPA re: HAWQS: Contract No: C_DOCCM130105CT0027 EP-G11H-00057 [pages 64-66]

Table 7. General percentage error calibration/validation targets for watershed models, applicable to monthly calibration (Donigian, 2002; Moriasi et al, 2007).

SWAT Output	Very Good	Good	Fair
Hydrology/Flow	<10	10-15	15-25
Sediment	< ± 15	± 15 to ± 30	± 30 to ± 55
Nutrients (TN & TP)	< ± 25	± 25 to ± 40	± 40 to ± 70

Kling-Gupta efficiency (KGE)

The KGE is the statistical tool that combines correlation, bias, and coefficients of variation in a balanced way and has been widely used in evaluating hydrological models in recent years (Gupta et al., 2009). The value of KGE ranges from -∞ to 1 where the value near 1 refers to a good fit of the model. KGE is calculated by:

$$KGE = 1 - \sqrt{(cc - 1)^2 + \left(\frac{cd}{rd} - 1\right)^2 + \left(\frac{cm}{rm} - 1\right)^2}$$

Where cc is the Pearson coefficient, cd is standard deviation of forecast values, rd is standard deviation of observation values, cm is average of forecast values, and rm is the average of observed values.

KGE captures three additional statistics: mean, standard deviation, and r^2 (coefficient of determination). In most cases, evaluation of KGE encompasses the conclusions that can be made from evaluating PBIAS and, to a lesser extent, NSE. Therefore, KGE was used as the primary calibration metric to evaluate model performance with values > 0.5 considered acceptable (Patil et al., 2015; Poméon et al., 2018).

SWAT-CUP

SWAT-CUP is a stand-alone, public domain program that assists during calibration and validation of SWAT models. There are currently five optimization algorithms that the user can select from to perform calibration and validation. The five algorithms are the Generalized Likelihood Uncertainty Estimation (GLUE), Sequential Uncertainty Fitting (SUF12), Parameter Solution (ParaSol), Markov chain Monte Carlo (MCMC) and Particle Swarm Optimization (PSO). SUF12 is the most flexible algorithm and the only algorithm that can be run with parallel processing within the SWAT-CUP program, therefore it was used to calibrate watersheds in HAWQS 2.0. The SUF12 algorithm performs parameter sensitivity and uncertainty analysis to identify which parameters contribute the most to the output variance relative to their input. A comprehensive description of the SUF12 algorithm can be found in Abbaspour et al. (2007).

Flow Calibration

After the model finished running on the HAWQS platform, the entire project was downloaded and a HUC12 SWAT-CUP project was created. The initial baseline scenario was first run through SWAT-CUP and the flow simulation was compared to the observational flow across the watershed. There were some differences between the observations and simulations indicating not only was calibration necessary, but also adjustments to some of the point sources were required.

Simulation Flow Updates

There were three subbasins within the watershed where the initial PBIAS values indicated the model was under simulating the flow. The SWAT model uses point source information, precipitation, and natural processes such as flow from the shallow aquifer returning into the stream flow (natural springs), among other processes to simulate flow. The under simulation of flow in these subbasins could be due to uncertainties in the point source data. To reflect the observed flow more accurately in these subbasins, the amount of baseflow was increased by 38mgd, 9.5mgd, and 6.6mgd in subbasins 8, 16, and 17, respectively. After adjusting the baseflow in these three subbasins, the PBIAS values from calibration for the gages in those subbasin were smaller. Once the baseflows were adjusted in the three subbasins, the entire model was ready for a complete calibration process in SWAT-CUP.

Results

In SWAT-CUP, the model was run varying 14 flow calibration parameters across the ranges outlined in Table 8. The parameter values resulting in the best fitted simulation for all 12 flow gages are also shown in Table 8. This one set of flow calibration parameters for the entire IRB watershed resulted in all 12 gages having acceptable calibration as shown in Table 9. Therefore, the model can reliably simulate the flow across the watershed.

Table 8. Range and best fitted parameters used for flow calibration for the IRB watershed.

Parameter Name	Description	Fitted Value	Minimum Value	Maximum Value
V__EPCO.hru	Plant uptake compensation factor	0.745	0.5	1
R__CN2.mgt	Initial SCS runoff curve number for moisture condition II	0.048	-0.1	0.1
V__ALPHA_BF.gw	Baseflow alpha factor	0.067	0.005	0.1
A__GW_DELAY.gw	Groundwater delay	1.25	-30	90
A__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur	937.50	-1000	1000
V__GW_REVAP.gw	Groundwater revap coefficient	0.046	0.02	0.1
A__RCHRG_DP.gw	Deep aquifer percolation fraction	-0.036	-0.05	0.05
A__REVAPMN.gw	Threshold depth of water in the shallow aquifer for revap to occur	-265.63	-750	750
V__ESCO.hru	Soil evaporation compensation factor	0.712	0.6	0.85
R__SOL_AWC(..).sol	Available water capacity of the soil layer	-0.014	-0.05	0.05
V__CANMX.hru	Maximum canopy storage	4.90	0	10
V__SLSOIL.hru	Slope length for lateral subsurface flow	17.19	0	150
V__LAT_TTIME.hru	Lateral flow travel time	0.73	0	14
V__ALPHA_BF_D.gw	Baseflow alfa factor for deep aquifer	1.00	0	1

R-indicates existing parameter value is multiplied by (1+fittedvalue), V- indicates existing parameter was replaced by the fitted value, and A-indicates existing parameter value is added by the fitted value.

Table 9. Flow calibration results for all 12 USGS gages.

			HUC12 Calibration Results					
State	Gage ID	Subbasin ID	R ²	NS	PBIAS	KGE	Sim. Mean	Obs. Mean
AR	07194800	3	0.87	0.86	-2.9	0.84	8.79	8.54
	07195000	8	0.87	0.85	-2.1	0.92	5.44	5.33
	07195800	16	0.65	0.63	3.5	0.8	0.87	0.9
	07195430	25	0.89	0.88	6	0.92	18.9	20.12
	07196900	27	0.79	0.79	-7.3	0.81	1.44	1.34
OK	07195865	17	0.87	0.81	11.3	0.69	0.82	0.92
	07196000	19	0.85	0.82	-7.9	0.87	3.79	3.51
	07195500	25	0.9	0.89	9.6	0.88	18.9	20.9
	07197000	35	0.86	0.86	-8.5	0.85	10.93	10.08
	07196090	37	0.92	0.92	-0.6	0.95	29.81	29.62
	07196500	39	0.89	0.88	8.3	0.87	28.74	31.35
	07197360	43	0.79	0.77	-11.6	0.83	3.16	2.84

To illustrate the accuracy of the flow calibration, Figure 5 shows the best estimation simulated time series compared with the observational data at USGS gage 07195430 located in Arkansas (subbasin 25). The model was able to simulate both the baseflow and the monthly variability, including high flow events, for the entire time period (2000-2020). The time series of best estimation simulation compared to observation for each of the USGS gages can be found in Appendix A: Model Simulation of Streamflow Compared to USGS Gage Streamflow

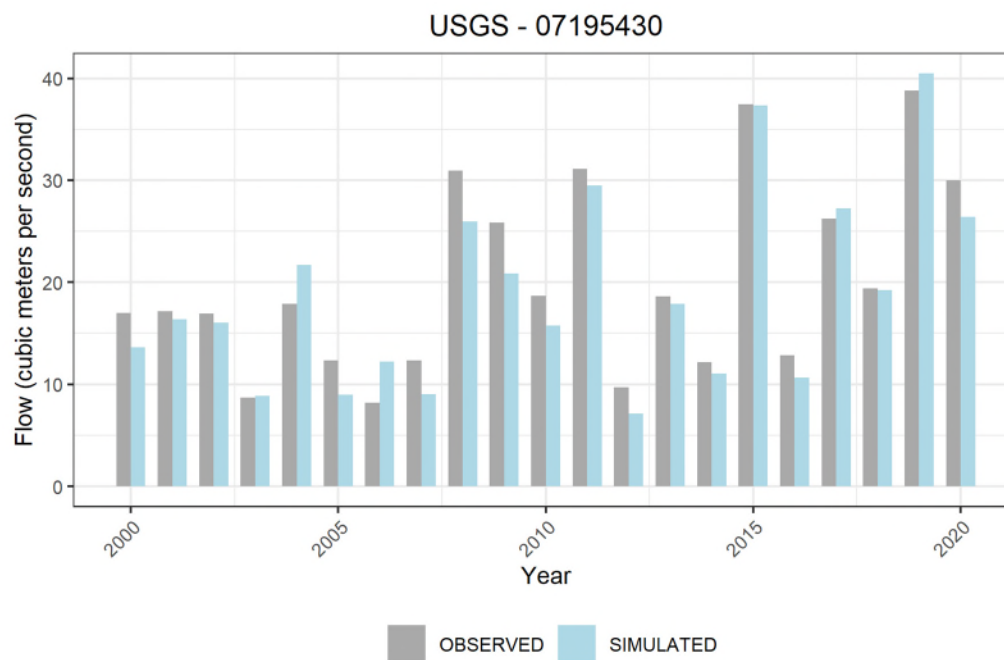


Figure 5. Comparison between the annually averaged observed (grey) and the simulated (blue) flow after calibration at USGS gage 07195430.

Water Quality Calibration

To accurately simulate WQ across the IRB, the management practices across the watershed were updated to reflect the most up-to-date practices for urban land, hog and dairy farms, poultry waste, and grazing cattle. These account for the vast majority of the phosphorus loading sources across the watershed.

Land Management Updates

Urban Management

The most impactful urban management within a watershed includes yard fertilization, watering, and mowing. Within the IRB model, the following values were selected using typical practices for urban land and applied to all urban land use types (URLD, URMD, URHD, and URTR):

- Urban land cover set to “growing”
- Land Cover ID set to “lawn”
- Initial leaf index set to 2
- Initial biomass set to 892 lbs/ac
- Number of heat units to bring lawn to maturity set to 2000
- Automatic Fertilization set using the following criteria:
 - Nitrogen application when stress factor falls below 0.8
 - Phosphorus application when stress factor falls below 0.5
- Automatic Irrigation set using the following criteria:
 - 1” of irrigation applied when soil moisture falls below 60%
- Mowing was set as follows:
 - Lawn mowed 6 times per growing cycle of grass

A summary of the amount of land within the IRB and each state, the range of nitrogen and phosphorus applied as fertilizer, and the amount of irrigation per application is found in Table 10.

Table 10. Summary of management on urban lawns in the IRB.

	IRB Watershed (acres)	Arkansas (acres)	Oklahoma (acres)	Nitrogen Application Range (lbs/ac)	Phosphorus Application Range (lbs/ac)	Irrigation per application (in.)
Urban Management	56,306	48,251	8,055	160 - 178	27 - 45	1

Hog and Dairy Farms

Both hog and dairy farms can contribute to the amount of nitrogen and phosphorus in the streams and rivers within a watershed, therefore it is important to include these facility locations in a model when calibrating WQ. Locations for eight hog farms and 10 dairy farms (Figure 6) in the AR side of the IRB were provided from FTN along with the manure application rate obtained from the DEQ Permit Data System (PDS). Upon close inspection of the values provided, there were large differences in the total amount applied per acre between farms, and there were locations that indicated they applied more phosphorus than nitrogen which is not consistent with the hog and dairy farm manure. Because of the discrepancies in the data received, the questionable locations were removed, and the remaining locations were averaged removing the highest and lowest application amounts. The resulting values (Table 11) were used for each farm within the watershed. Since the HRUs selected to simulate the hog and

dairy farms were not the exact same area (number of acres) as the actual farms, an area weighted value of application rate was used. This was done to accurately account for the manure for each farm.

To represent the hog and dairy farms in the IRB model, the corresponding pastures of the locations for each farm (total area is shown in Table 11) was set with the following management schedule:

- In March:
 - Plant Bermudagrass
- In March, June, September, and December:
 - Apply Nitrogen and Phosphorus
 - Harvest Grass

Table 11. Amount of pasture land modeled for Hog and Dairy Farm manure and the rate of application.

	Area (acres)	Nitrogen Applied per application (lbs/ac)	Phosphorus Applied per application (lbs/ac)
Total Pasture Area	427,417		
Applied Hog Manure	3623.5 (0.85%)	146.3	102.5
Applied Dairy Manure	1028.5 (0.24%)	353.6	155.0

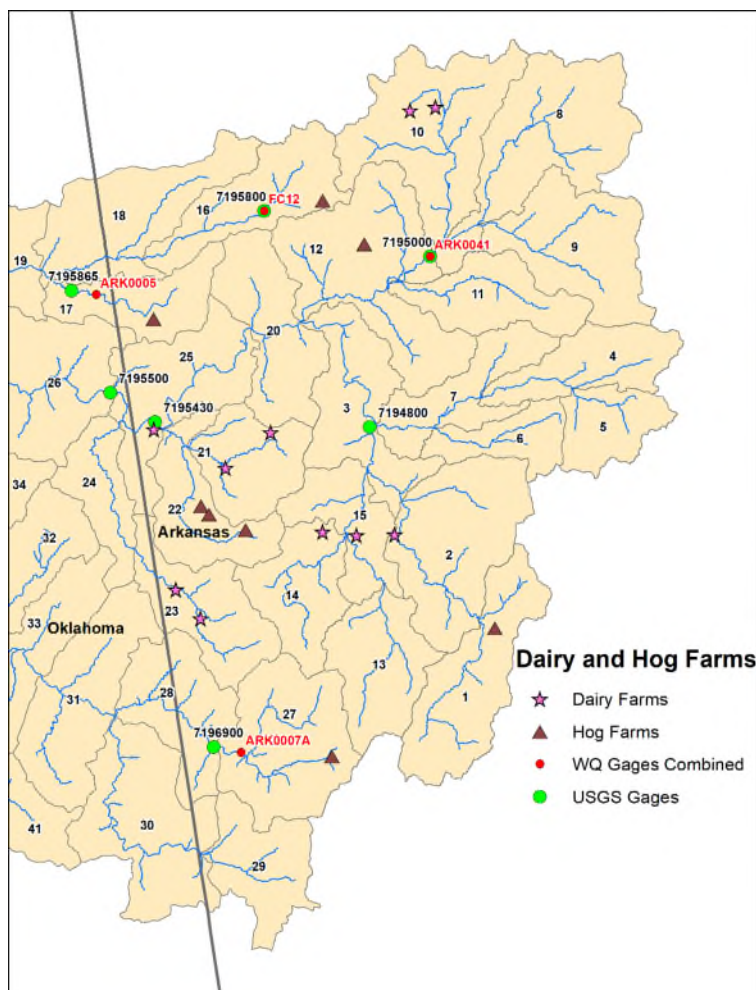


Figure 6. The locations of Dairy and Hog farms in the AR side of the IRB.

Poultry Litter

A main concern for pollutants in the water in the IRB is from the application of poultry waste within the watershed. To model poultry waste land application, information on the location of bird farms, number of bird farms, total birds at each farm, the amount of manure produced, the amount transported out of the watershed, and the amount applied annually was necessary. The Oklahoma Conservation Commission (OCC) provided a GIS layer of active poultry houses created using 2018 data from the Oklahoma Department of Agriculture, Food and Forestry and satellite imagery from 2022 across IRB (Figure 7). From this layer, it was determined that there were 466 houses (97 farms in OK) and 1,345 houses (281 farms in AR). OCC also provided information that a typical bird house in the IRB has 5 cycles of birds for 45 days each. Based on the information provided on the number of birds per house across the OK side of the IRB the following average values were used for all bird houses in AR and those in OK that did not have bird per house values within the IRB.

- Houses >10 = 46,000 birds per house
- Houses ≤10 = 24,000 birds per house

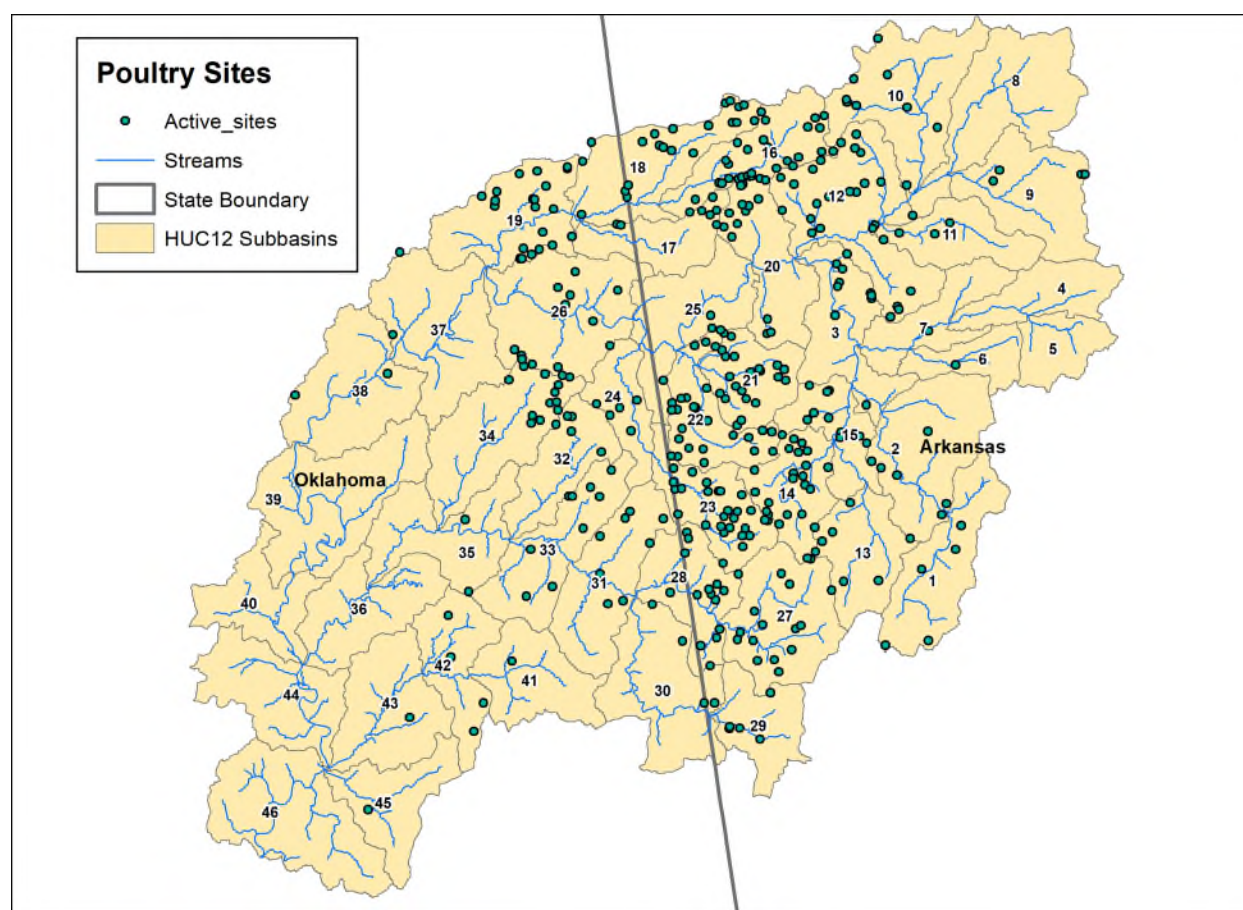


Figure 7. Location of active poultry house sites used to calculate total poultry waste produced across the IRB.

Using these values, the total bird count for the IRB was 234,557,040 with 181,530,000 in AR and 53,027,040 in OK. According to the Poultry Federation¹⁵ for 2021, the entire state of AR produced ~1 billion birds and the state of OK produced about 200 million birds. Using the calculated number of birds from above, this indicates that about 17% of the total AR birds are from the IRB and about 26% of the total OK birds are from the IRB. The

¹⁵ https://www.thepoultryfederation.com/images/2021_Poultry-Production__Value.pdf

Poultry Federation¹⁶ also indicates most poultry farms are in northwest AR and the eastern third of the state of OK, where the IRB is located, therefore these values, although potentially conservative, are used to calculate the amount of manure produced in the basin.

To calculate the manure amounts produced by the 234.5 million birds, all birds were considered as broilers with a manure production rate of 22 g/day-bird.¹⁷ The total manure (M) production was calculated as:

$$M_{Year} = 234,557,040_{birds} * 22g_{/day-bird} * 45_{days} * 1.1e^{-6}_{ton/g}$$

$$M_{Year} = 255,969_{tons}$$

For purposes of the IRB model, OCC recommended using an estimated rate that 50% of all poultry waste is exported out of the watershed leaving the remaining 50% as applied poultry waste (AM):

$$AM_{Year} = 255,969_{tons} * 0.5$$

$$AM_{Year} = 127,985_{tons}$$

Additionally, OCC recommended using an amount of 3 tons/acre of poultry waste applied once in March. These values were transferred into the model assuming that poultry waste was applied in proximity to the poultry houses within each subbasin based on OCC's conclusion that poultry waste was not transported far from farms when applied. Pastures within each subbasin were selected until the total area was close to the area required for the 50% application using 3 tons/acre. The total applied poultry waste in the model was 126,696 tons/year, which was slightly less than the target 50% (49.5%). Using the 3 tons/acre application rate once a year, 42,232 acres (~10%) of pasture land received poultry waste application across the IRB. Table 12 summaries the distribution of the pasture land receiving poultry waste by state. Additionally, OCC recommended using a value of 200 lbs/acre of nitrogen in May and September as supplementation of the nutrients in the fields.

The pasture land that received poultry waste in the model was also modeled with cattle grazing, therefore the details of the pasture land simulating poultry waste land application is detailed in the "Grazing Cattle" section below.

Table 12. Amount of land receiving poultry waste in the basin and with each state along with the amount poultry waste and nitrogen fertilizer.

	IRB Watershed (acres)	Arkansas (acres)	Oklahoma (acres)	Nitrogen (lbs/ac)	Poultry Waste per application (lbs/ac)
Total Pasture Area	427,417	251,543 (58.9%)	175,873 (41.1%)		
Applied Poultry Litter	42,232 (10%)	32,448 (12.9%)	9,783 (5.6%)	200	6,000 (3 tons/ac)

Grazing Cattle

Any pasture land within the IRB that was not previously modeled as a hog or dairy farm was modeled with grazing cattle. According to the Oklahoma State University Extension¹⁸ one cow ~ 1 AU (1000 lbs) and needs 26 lbs dry forage a day. Additionally, they suggest 75% utility for bermudagrass, a warm season grass commonly

¹⁶ <https://www.thepoultryfederation.com/resources/facts-figures>

¹⁷ <https://engineering.purdue.edu/adt/PoultryManure/PurduePoultryDayPoster8-28-12.pdf>

¹⁸ <https://extension.okstate.edu/fact-sheets/stocking-rate-the-key-to-successful-livestock-production.html>

grown in the watershed. According to Hamberg et al., 2010, cows trample ~50% of what they eat (13 lbs), and OCC stated a typical pasture in the IRB produces ~5,000 lbs/acre.

To determine the distribution of pasture land under well managed grazing and over grazing, Mittelstet et al., (2016), used Landsat 4-5 Thematic Mapper imagery from 2010-2011 to calculate the Normalized Difference Vegetation Index (NDVI) across the IRB for pasture classification.¹⁹

$$NDVI = (NIR - VIS) / (NIR + VIS)$$

Where VIS is the spectral reflectance in the visible red region and NIR is the near-infrared region of the electromagnetic spectrum. An unsupervised landcover classification was done with 2010 NAIP (National Agricultural Imagery Program) aerial images as well as September 2011 ground truth data for validation. Additionally, a field verification was repeated by OCC in 2023 using Google Earth imagery and ground truth data for a more recent validation of the pasture land distribution across the IRB. The resulting pasture land distribution between well managed pastures and overgrazed pastures is shown in Figure 8.

Based on the amount of available pasture biomass, well managed pastures were simulated using 220 days of grazing while an overgrazed pasture allowed cattle to graze for 270 days. Using the distribution of pasture land according to Mittelstet et al., (2016), pasture land modeled in the IRB was divided within each subbasin using the fraction between well managed and over grazed land for each subbasin. Within each subbasin, land was selected that a) were not already used for hog or dairy, b) had a soil type that matched our map of grazing lands, c) consisted of pasture land, and d) summed as close as possible to the targeted area. This process resulted in a similar ratio of 65.5% well managed and 34.5% over grazed across the watershed. Table 13 details the amount of pasture land within the IRB and each state for well managed with and without poultry, and overgrazed pastures with and without poultry.

The amount of pasture land modeled for cattle grazing with the IRB was 422,765 acres. To determine the stocking rate of the cattle, first the total amount of available forage (F) was calculated.

$$F_{lbs} = 422,765_{acres} * 5,000 \frac{lbs}{acre} * 0.75_{utilization}$$

$$F = 1,585,368,750_{lbs}$$

Next, the total head of cattle (TC) was calculated using the daily forage and trampling, the number of days for well managed and overgrazed, and the ratio of land for well managed and overgrazed as follows:

$$TC_{heads} = \frac{F_{lbs}}{[220_{days} * (26_{lbs} + 13_{lbs}) * 0.655] + [270_{days} * (26_{lbs} + 13_{lbs}) * 0.345]}$$

$$TC = 171,340_{heads}$$

Finally, a stocking rate was calculated by dividing the total head of cattle (TC) by the total area for grazing pasture land (422,765 acres) resulting in a stocking rate of 2.5 acres/cattle or 0.4 cattle/acre. This stocking rate is consistent with OCC input on common stocking rates across the IRB. Additionally, the TC calculated is consistent with the 2017 NASS census.^{20;21} The number of cattle was estimated from the census weighted by the area of each county in the IRB (~150,000 heads).

Values in the model for grazing cattle are based on the stocking rate of the cattle and the available biomass for grazing.

¹⁹ Development of Current Digital Land Use Data Using 30 m TM (Landsat 5) Imagery for the Illinois River (Range_calss_methods_Appendix A)

²⁰ https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/County_Profiles/Oklahoma/index.php

²¹ https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/County_Profiles/Arkansas/index.php

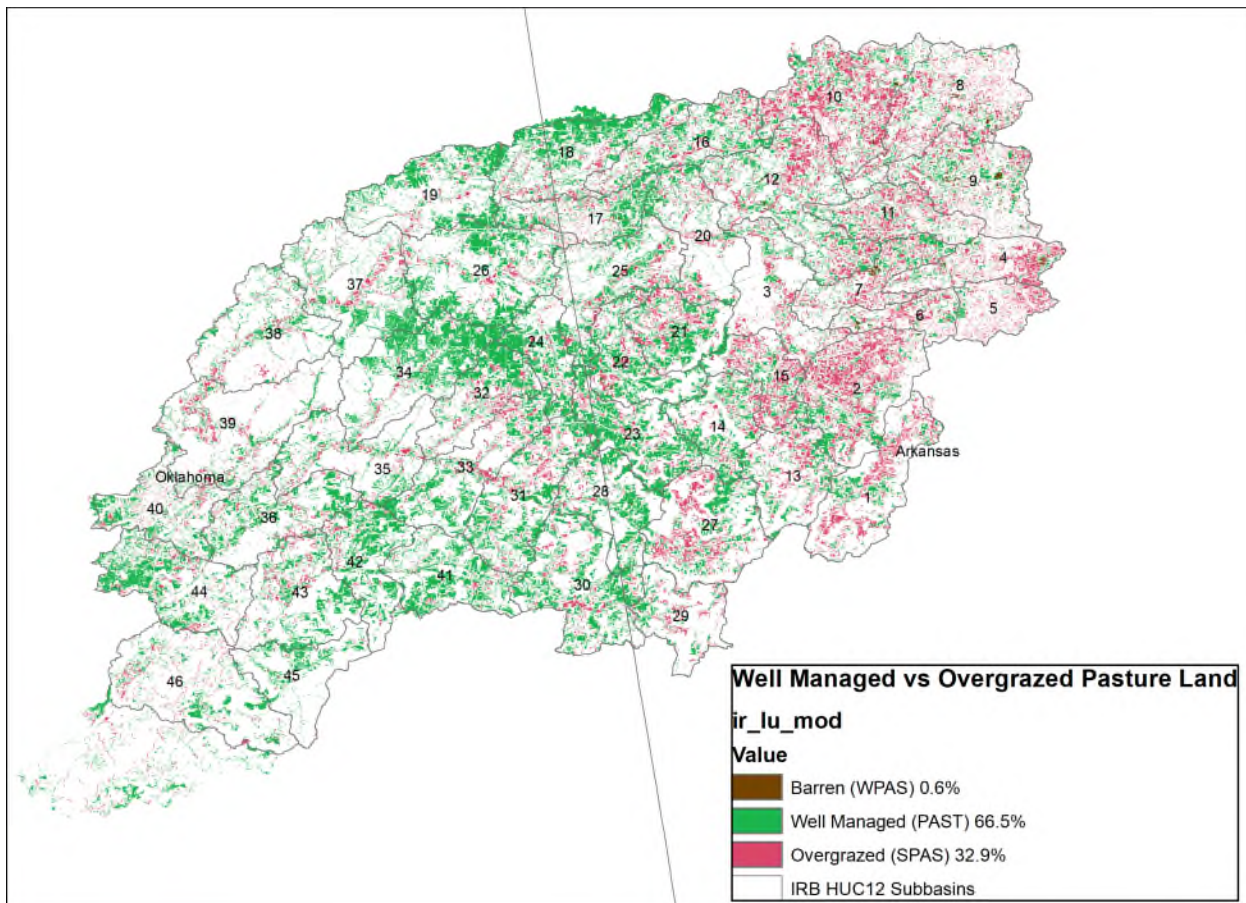


Figure 8. Representation of well managed vs overgrazed pasture land (Mittelstet et al., (2016)) across the IRB.

All HRU management files for pasture land where grazing cattle was modeled were updated with the following settings:

- Land Cover ID set to bermudagrass
- Initial biomass set to 892 lbs/ac
- Number of heat units to bring lawn to maturity to 2,000
- Biomass eat dry weight 26 lbs/ac/day
- Biomass trample dry weight 13 lbs/ac/day
- Manure deposited dry weight 10.3 lbs/ac/day

For HRUs of pasture land that also received poultry waste, the management files were updated as follows:

- 3 tons/acre poultry waste applied:
 - 4/15 for well managed
 - 3/1 for over grazed
- 200 lbs/acre Nitrogen applied on 5/1 and 9/1
- Harvest only (HARVEFF = 0.8) on 12/15

For HRUs of pasture land with well managed grazing, the management files were updated as follows:

- Minimum biomass for grazing 1,070 lbs/ac
- Grazing from 4/20 – 11/6 (220 days)

For HRUs of pasture land with overgrazing, the management files were updated as follows:

- Minimum biomass for grazing 714 lbs/ac
- Grazing from 3/15 – 12/10 (270 days)

Table 13. Summary of the amount of pasture land used for cattle grazing with and without the application of poultry waste.

	IRB Watershed (acres)	Arkansas (acres)	Oklahoma (acres)
Total Pasture Area	427,417	251,543 (58.9%)	175,873 (41.1%)
Grazing Cattle Total	422,765 (98.9%)	246,891 (98.2%)	175,873 (100%)
Well Managed with Poultry Litter	24,732 (5.9%)	19,452 (7.9%)	5,280 (3.0%)
Well Managed	251,514 (59.5%)	114,154 (46.2%)	137,360 (78.1%)
Over Grazed with Poultry Litter	17,500 (4.1%)	12,997 (5.3%)	4,503 (2.6%)
Over Grazed	129,018 (30.5%)	100,289 (40.6%)	28,730 (16.3%)

Results

Once all the management files across the IRB were updated, the model was run through SWAT-CUP for calibration of SSC, P, and TN. Since the model was previously calibrated for flow, all 14 flow calibration parameters were held constant using the best fitted values. The WQ calibration was done in three steps, first SSC was calibrated by varying the first 6 calibration parameter associated with sediment across the range outlined in Table 14. After the best fitted values for all 12 gages were found, then SWAT-CUP was run again, this time holding flow and sediment calibration parameters constant with the best fitted values, and varying the next 5 parameters in Table 14 associated with P. Finally, this process was replicated again, but this time for N using the remaining 6 calibration parameters from Table 14.

Table 14. Range and best fitted parameter values for water quality calibration for the IRB watershed.

Parameter Name	Description	Fitted Value	Minimum Value	Maximum Value
v__CH_COV1.rte	Channel erodibility factor	0.32	0.3	0.7
v__CH_COV2.rte	Channel cover factor	0.015	0.005	0.2
v__SPCON.bsn	Maximum amount of sediment that can be reentrained	0.003	0.0001	0.01
v__SPEXP.bsn	Sediment reentrained in channel sediment routing	1.589	1.0	2.0
v__ADJ_PKR.bsn	Peak rate adjustment factor for sediment routing in the subbasin	0.727	0.5	2.0
v__PRF_BSN.bsn	Peak rate adjustment factor for sediment routing in the main channel	0.635	0	2.0
v__P_UPDIS.bsn	Phosphorus uptake distribution parameter	77.292	20	100
v__PPERCO.bsn	Phosphorus percolation coefficient	13.28	10	17.5

v__PHOSKD.bsn	Phosphorus soil partitioning coefficient	179.69	120	200
v__PSP.bsn	Phosphorus sorption coefficient	0.6	0.01	0.7
v__ERORGP.hru (Pasture)	Organic phosphorus enrichment ratio	0.32	0	5
v__CDN.bsn	Denitrification exponential rate coefficient	1.1104	1.0	1.2
V__CMN.bsn	Rate factor for humus mineralization of active organic nitrogen	0.0025	0.001	0.003
v__NPERCO.bsn	Nitrogen percolation coefficient	0.9896	0	1.0
V__RSDCO.bsn	Residue decomposition coefficient	0.0748	0.02	0.1
V__SDNCO.bsn	Denitrification threshold water content	0.929	0.6	1.0
V__N_UPDIS.bsn	Nitrogen uptake distribution parameter	94.792	0	100

R-indicates existing parameter value is multiplied by $(1 + \text{fittedvalue})$, *V*- indicates existing parameter was replaced by the fitted value, and *A*-indicates existing parameter value is added by the fitted value.

Phosphorus

Calibration of total phosphorus showed mixed results across the IRB watershed (Table 15). Eight out of twelve the locations did have acceptable PBIAS values showing, once again, that the model was successful at modeling the magnitude of the total phosphorus loading across most of the watershed. When looking at the monthly variability, five of the locations were moderately successful.

Error! Reference source not found. shows the comparison of the LOADEST generated total phosphorus compared to the model simulated total phosphorus after calibration for the USGS gage 07196500. This is an example of how the annual loading is represented well (smaller PBIAS value) and most of the variability is also modelled (acceptable NSE and KGE). The annual time series of total phosphorus best estimation simulation compared to the observations generated through LOADEST for each of the USGS gages can be found in Appendix B: Model Simulation of Total Phosphorus Loading in the Watershed Compared to LOADEST Input Generated from Grab Sample Observations.

There are some uncertainties in the model that can account for poor calibration of these few gages in the watershed. Nevertheless, the model is scientifically acceptable and able to reliably capture the spatial and temporal variability across the watershed for 8 out of 12 gages. The uncertainty in the remaining gages is attributable to limited observations during high flow and uncertainty from the LOADEST loadings, uncertainties in the point source data, and the initialization of the soil soluble phosphorus values in the model. Importantly, when calibrating the model for an entire watershed it is not unusual to have the majority of the gages agreeing with model results and other gages having uncertainties due to issues with observations and sample monitoring. Indeed, even with these limitations, such models are scientifically valid for estimating the phosphorus loading under various land uses and management conditions (Harmel et al., 2006; Harmel and Smith 2007).

Table 15. Calibration summary statistics for total phosphorus (TP) across the IRB watershed.

						TP		
State	HUC12 Subbasin	HUC12 ID	USGS Gage/ Combined	area diff.	WQ Time Period	NSE	PBIAS	KGE
AR	3	111101030103	07194800	1.57	10/2001-12/2020	0.4	-6.9	0.29

	8	111101030305	07195000-ARK0041	1.00	01/2000-12/2020	0.35	6	0.42
	16	111101030501	07195800 (FC12)	2.06	07/2009-06/2015	-0.1	-221	-1.23
	25	111101030606	07195430	1.10	01/2000-12/2020	-0.41	-130.9	-0.41
	27	111101030701	07196900-ARK0007A	1.01	01/2000-12/2020	-1.06	-189.1	-1.03
OK	17	111101030502	07195865-ARK0005	1.14	01/2000-12/2020	0.1	56.7	-0.06
	19	111101030504	07196000	1.09	01/2000-12/2020	0.47	-48.1	0.39
	25	111101030607	07195500	1.00	01/2000-12/2020	-0.25	-118	-0.28
	35	111101030709	07197000	1.00	01/2000-12/2020	0.38	-0.8	0.29
	37	111101030802	07196090	1.04	06/2010-12/2020	0.61	-45.5	0.38
	39	111101030804	07196500	1.00	01/2000-12/2020	0.55	-22.5	0.46
	43	111101030903	07197360	1.05	01/2000-09/2010	0.41	-48.4	0.37

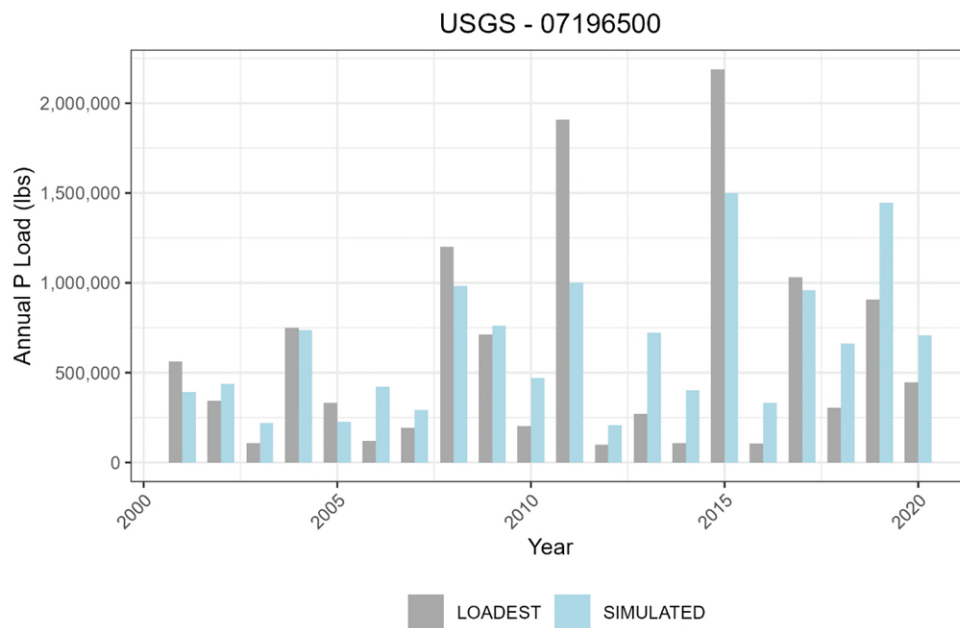


Figure 9. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07196500 and subbasin 25.

Figure 10 shows the total phosphorus loading from each subbasin within the IRB watershed both as per acre and as total loading. This shows that the subbasins that are receiving most of the poultry waste land application (see Figure 19) are also showing the largest amount of total phosphorus loading per acre within the subbasin.

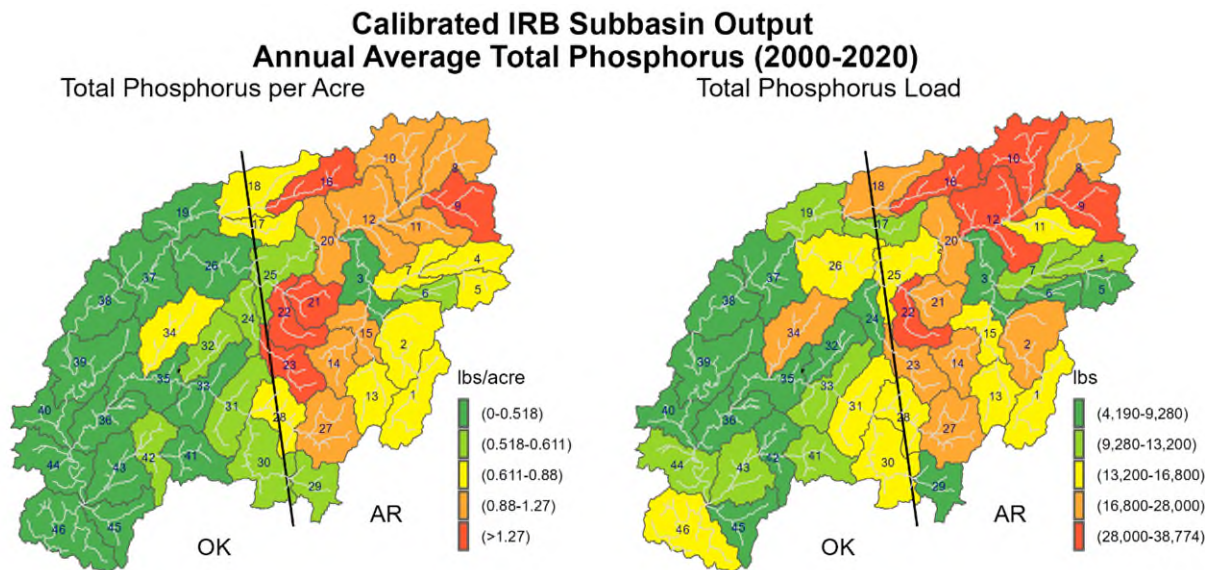


Figure 10. Annual average loading of total phosphorus from each subbasin in the IRB watershed.

LOADING BY LAND USE

The total amount of loading for each land use type is found in Table 16. Overall, there is about 1 million pounds of phosphorus from all land use types across the entire IRB watershed. When looking at the various types of land uses, most of this loading is from pasture land (~ 83%). Forest land is the next highest contributor followed by urban land use however they are a small fraction of the total contributing load. Table 17 provides a detailed analysis of the type of management on pasture lands and the associated amount of phosphorus loading based upon the calibrated model with default soil soluble phosphorus values.

Table 16. Total amount of phosphorus loading by land use type across the IRB.

	Area (Acres)	Total Phosphorus (lbs/acre)	Total Phosphorus (lbs)	% of Total Phosphorus Load
All Land Use	981,961	1.04	1,023,292	
Forest	460,387	0.20	90,333	8.8%
Pasture	427,417	1.98	845,903	82.7%
Urban	56,306	1.17	66,095	6.5%
Range/Shrub	21,846	0.46	10,046	1.0%
Other	16,005	0.68	10,915	1.1%

Table 17. Average concentration and load of phosphorus across pasture land classification within the IRB watershed.

	Percent of Pasture	Area (Acres)	Total Phosphorus (lbs/acre)	Total Phosphorus (lbs)
Average of All Pasture Land		427,417	1.98	845,903
Dairy Farms	0.24%	1,028	4.46	4,592
Hog Farms	0.85%	3,623.5	3.15	11,412
Over Grazed	30.2%	129,019	2.11	272,603
Well Managed	59.9%	251,514	1.44	361,293
Litter Well Managed	5.8%	24,732	3.55	87,708
Litter Over Grazed	4.1%	17,500	6.19	108,295

The pasture land that is receiving poultry waste application (10% of the pasture land) is producing about ~23% of the total phosphorus loading; moreover, the area that is receiving poultry waste application (10% of the pasture land) is contributing 247-293% more phosphorus per acre than the land that does not receive any poultry waste application.

OPINIONS AND DETAILED RESPONSES TO 8 QUESTIONS

QUESTION 1

1. What can the SWAT model tell us about trends in the phosphorus loading and phosphorus concentrations occurring in the rivers and streams of the Illinois River Watershed in Oklahoma since 2010?

Daily phosphorus loading averaged yearly from 2010-2020 shows an increase in trend along tributaries and the main channels of the Illinois River leading into Lake Tenkiller.

This increasing trend is also evident in the phosphorus concentration over most of the watershed, with a few locations showing a decrease in concentration. These locations in the watershed with decreasing concentration are likely due to an increase in flow. There is also an increase in precipitation over the past 10 years that contributes more total phosphorous into the river and lake.

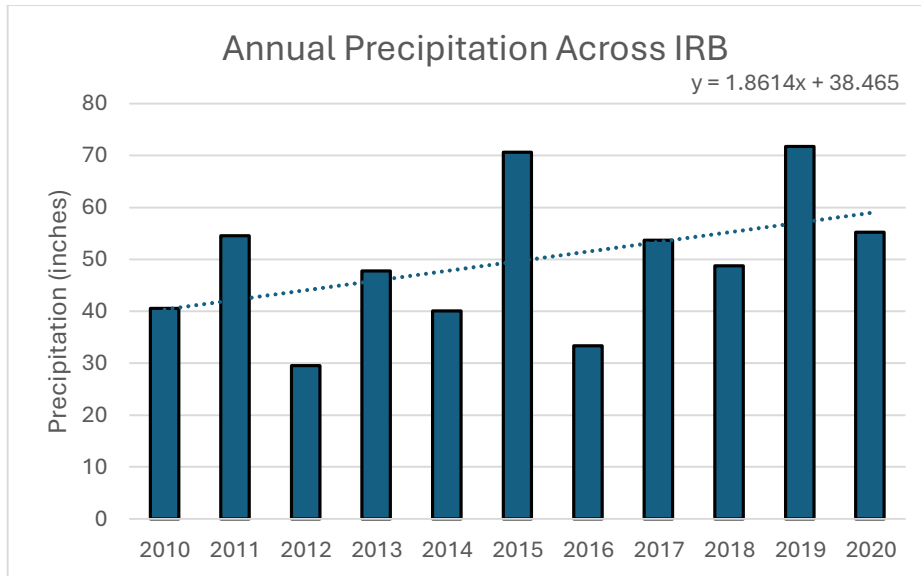


Figure 11. Annual precipitation in the IRB from 2010-2020.

The concentration of total phosphorus across the entire watershed from 2010-2020, is well above the scenic water quality standard of 0.037 mg/l for the state of Oklahoma.

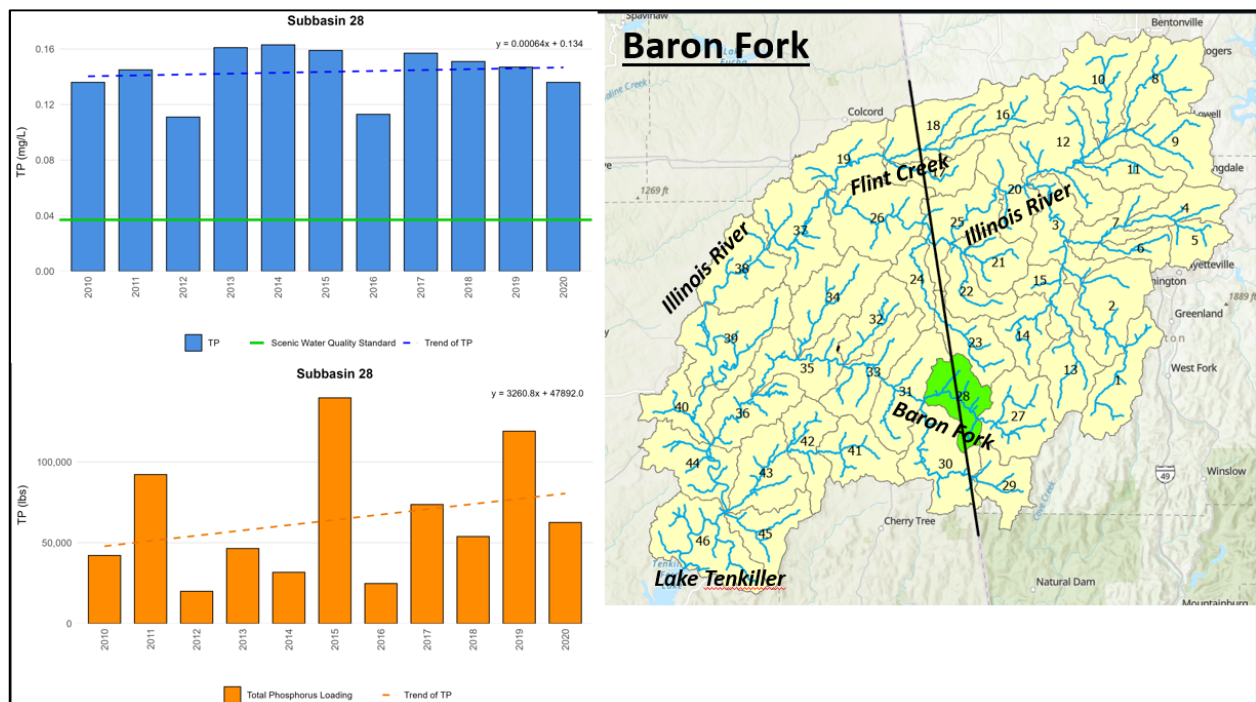


Figure 12. Total phosphorus (TP) concentration (top) and loading (bottom) in Subbasin 28- Baron Fork.

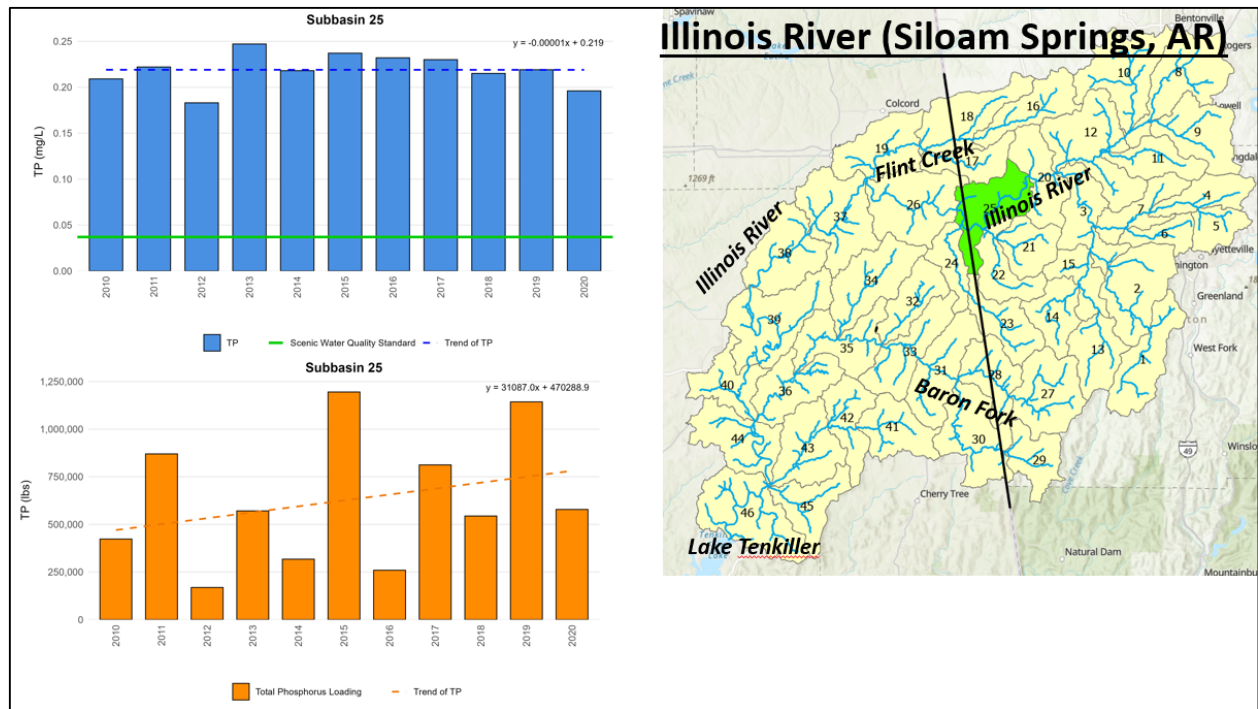


Figure 13. Total phosphorus (TP) concentration (top) and loading (bottom) in Subbasin 25 - Illinois River Siloam Springs, AR.

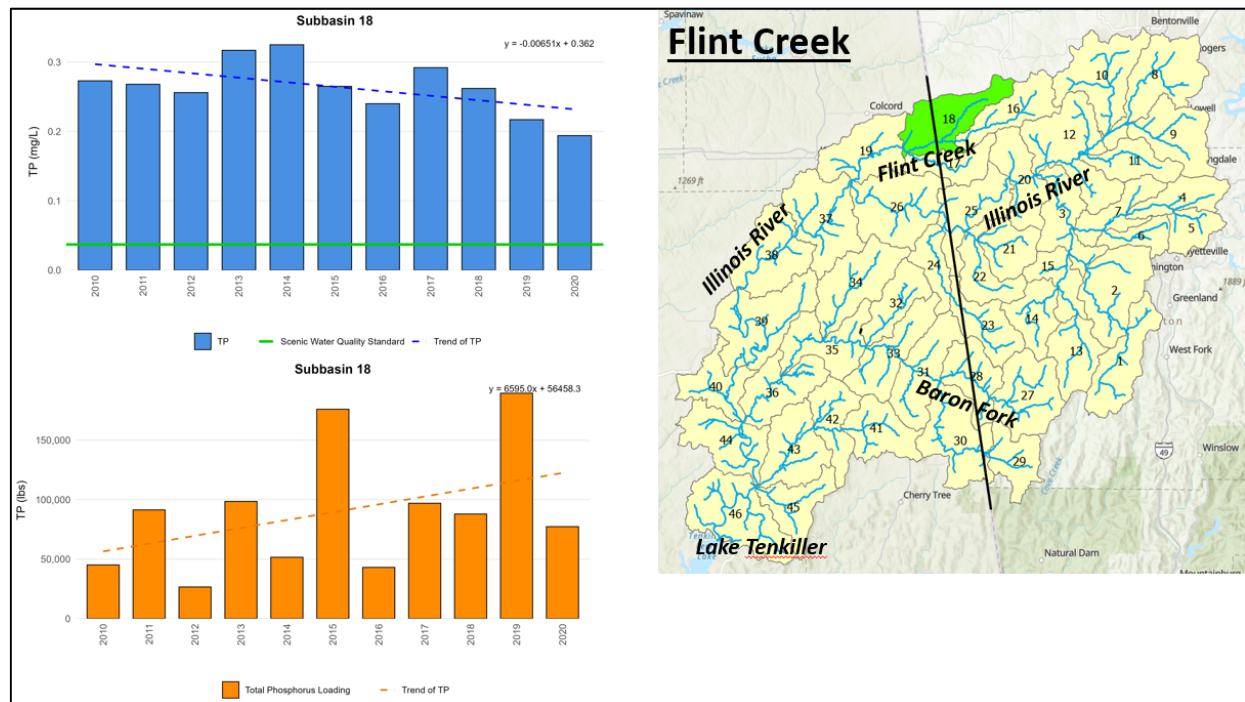


Figure 14. Total phosphorus (TP) concentration (top) and loading (bottom) in Subbasin 18 – Flint Creek.

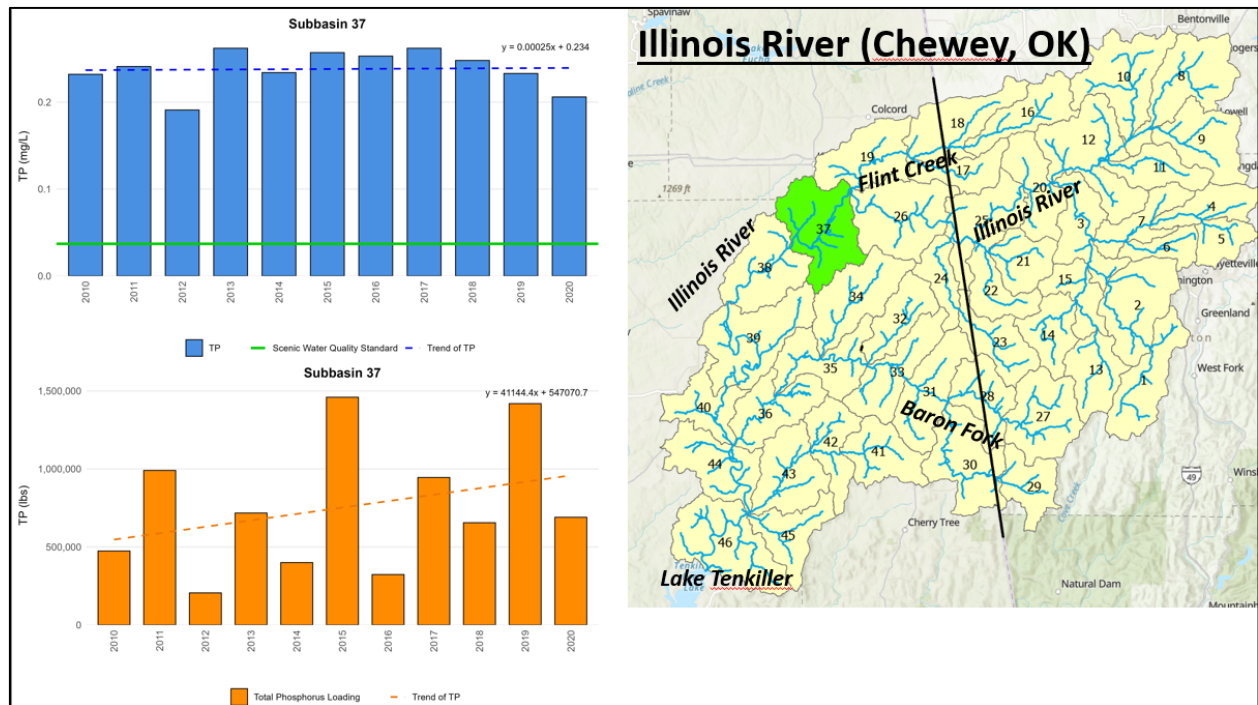


Figure 15. Total phosphorus (TP) concentration (top) and loading (bottom) in Subbasin 37 - Illinois River (Chewey, OK).

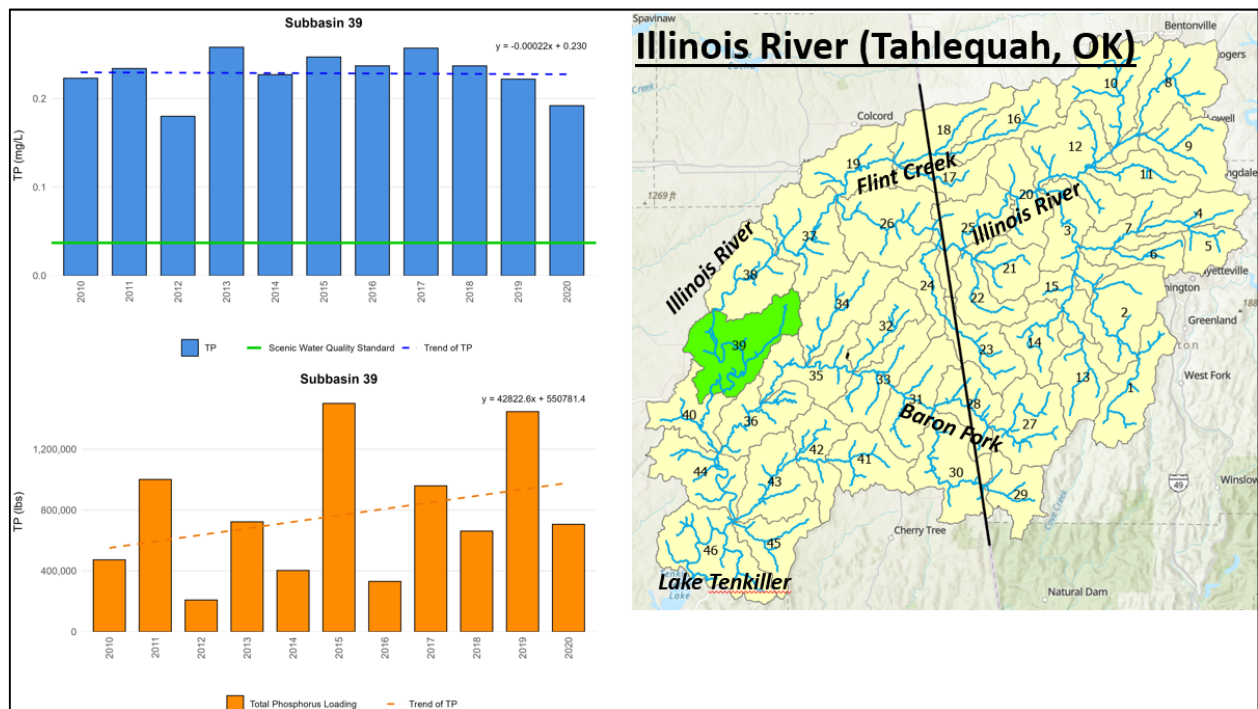


Figure 16. Total phosphorus (TP) concentration (top) and loading (bottom) in Subbasin 39 - Illinois River (Tahlequah, OK).

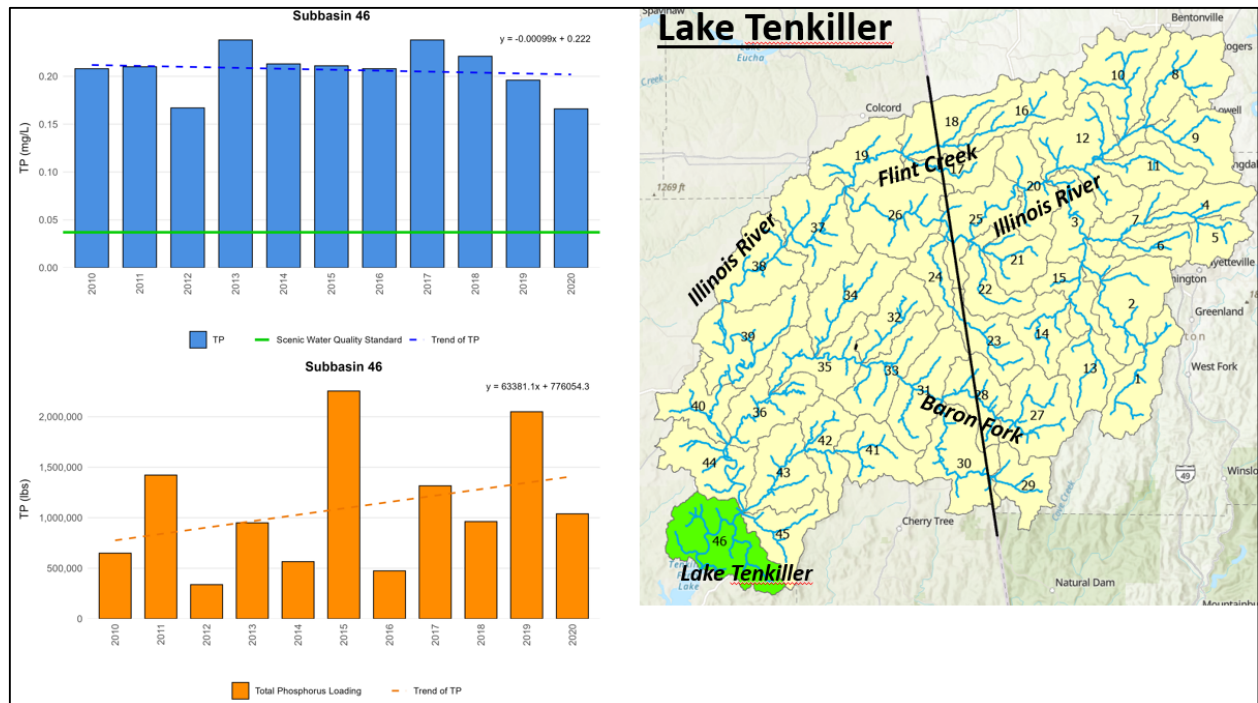


Figure 17. Total phosphorus (TP) concentration (top) and loading (bottom) in Subbasin 46 - Lake Tenkiller.

The average annual phosphorus loading into the rivers across the watershed and into Lake Tenkiller is shown below. The land with poultry houses, where poultry waste land application is simulated, is contributing to the phosphorus loading to the headwaters of the rivers and streams, and that is accumulating as it flows downstream ending up in Lake Tenkiller.

Annual Average TP Loading from 2010-2020

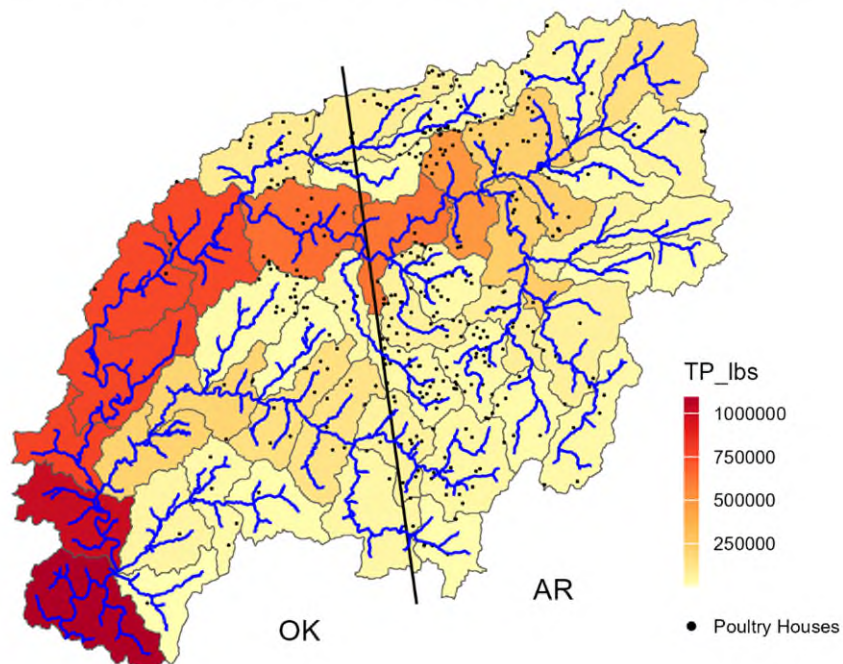


Figure 18. Annual Average Loading of Total Phosphorus (TP) from 2010-2020.

QUESTION 2

2. What can the SWAT model tell us about whether phosphorus from poultry waste land application – both historic and current – is a significant contributor to current phosphorus loading in the rivers and streams of the Illinois River Watershed in Oklahoma?

Both historic poultry waste land application in the IRB and current poultry waste land application are significant contributors to the current phosphorus loading to the rivers and streams in the IRB.

Current:

The IRB model models the presence of 1,345 poultry houses. Farms with 10 or less houses were assigned 24,000 birds per house, and farms with more than 10 houses were assigned 46,000 birds per house. There were 5 cycles of birds for 45 days each resulting in a total bird count of 234,557,040 birds. The value of poultry waste production for a broiler of 22 g/day-bird was used resulting in 255,969 tons of poultry waste per year generated. The model targeted 50% of this poultry waste for application. These values were transferred into the model assuming that poultry waste was applied in proximity to the poultry houses within each subbasin. Pastures were selected until the total area was close to the area required for the 50% application using 3 tons/acre. The final amount of poultry waste applied in the model was slightly lower than the 50% target (49.5%). A total of 126,695.25 tons or 253,390,500 lbs of poultry waste was applied. This model simulated this application amount annually and was simulated from 2000 to 2020.

IRB Yearly Poultry Waste Land Application

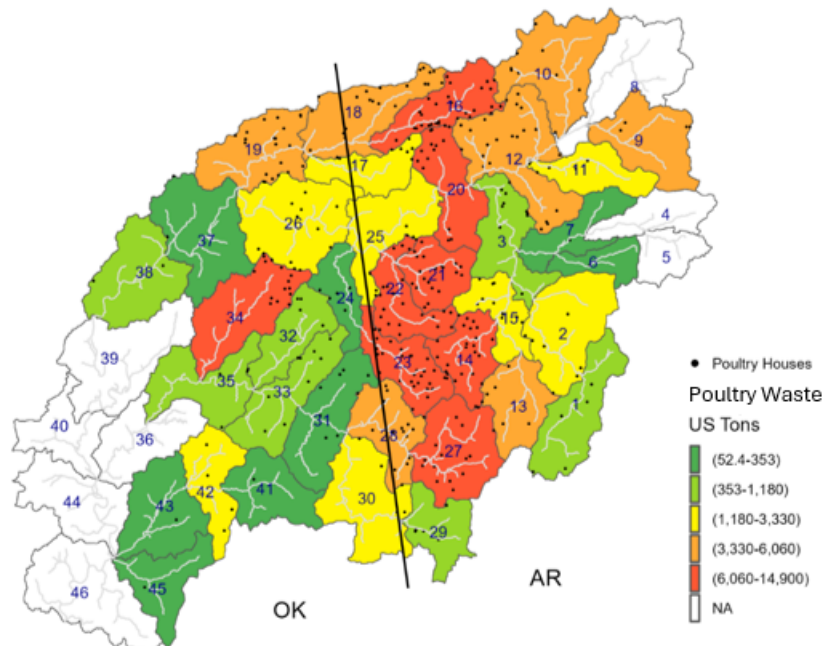


Figure 19. Tons of poultry waste applied yearly in the IRB model.

The total phosphorus in the poultry waste applied is 0.019 kg/kg of poultry waste (The phosphorus ratio of poultry waste used in our model is ~ 1 to 2, 0.006 kg/kg of soluble phosphorus to 0.013 kg/kg organic phosphorus). This is equivalent to 4,814,419.5 lbs of total phosphorus applied per year.

The model simulated an annual average amount of total phosphorus that remained in the soil of 958,423 lbs.

So, 20% of the total phosphorus from the poultry waste applied in the watershed remains in the soil year after year.

The average annual total phosphorus loading into the river from land with poultry waste applied was 196,003 lbs for the 2000 to 2020 simulation which was initialized with default soil phosphorus values, not the actual soil phosphorus values.

This results in a total annual average of 1,154,426 lbs of total phosphorus from poultry waste, or 24% of the total phosphorus of the poultry waste applied, remaining in the watershed either in the soil (20%) as legacy phosphorus or runoff from the land to the nearest creeks or streams (4.1%) as loading every year.

For example, this figure shows the initial values of soluble phosphorus used in the model in subbasin 25, and the change over time in the soil of the pastures with four different management practices.

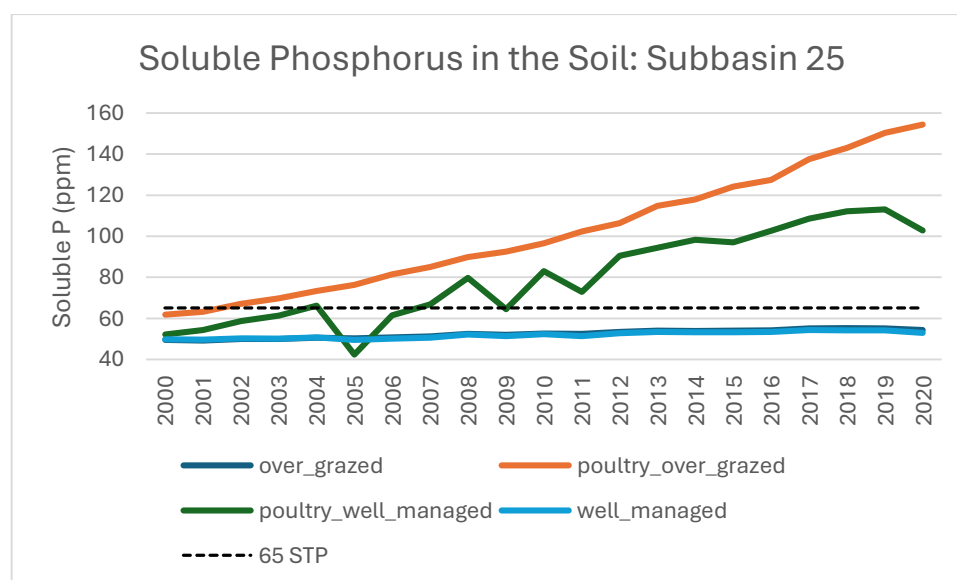


Figure 20. Soluble Phosphorus (P) in the soil in Subbasin 25 for 4 different management practices. The 65 STP goal is marked with a black dashed line.

In our model, we used the default values of phosphorus and nitrogen components in the soil as initial values at the beginning of the simulation. These values are internally estimated based on the amount of soil carbon in the type of soil based on properties from soil testing developed by USDA NRCS federal database. This database was developed in the 1950-60s, which would pre-date any extensive mechanized poultry waste operations in the watershed. Hence, these values are very likely low compared to actual 2000 values. Other studies in the IRB have used soluble phosphorus values from testing done in the early 1990s (Storm et al 2006) however, setting only the soil soluble phosphorus values without setting the organic phosphorus and nitrogen values can cause uncertainty in the model output. Therefore, since there was not a federally approved database for soil components of phosphorus and nitrogen, the default values were used instead. These default values may not directly simulate the real levels of phosphorus in the soil; however, they will accurately simulate what happens to the amount of phosphorus in the soil and the amount of phosphorus entering the waterways under the management practices simulated.

The initial soil soluble phosphorus default values in the model ranged from 18 ppm to 61.6 ppm on pasture land where poultry was applied. After 11 years of poultry waste application the range increases to 51ppm to 95 ppm. After an additional 10 years (that is 21 years of application) the range increases again

to 46.6²² to 152.7 ppm. This is on average about an 118% increase in 11 years and 152% increase in 21 years on pasture land where poultry was applied.

If the soil soluble phosphorus values from Storm et al 2006, which ranged from 123 ppm to 197 ppm, were used in this model, the resulting range of soluble phosphorus values in the soil would be closer to 197 ppm to 299 ppm. So, the IRB model presented here is a conservative model, and the magnitude of phosphorus in the soil understates the ground truth conditions.

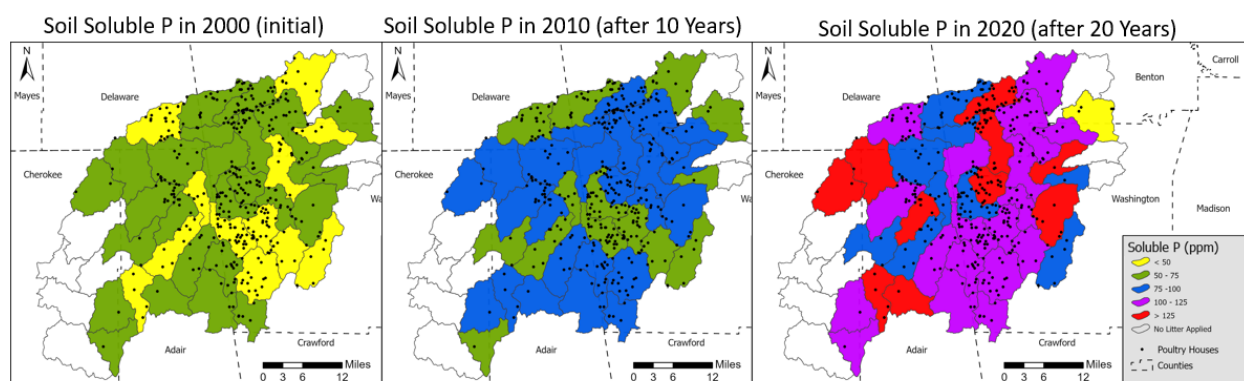


Figure 21. Soluble Phosphorus (P) in the soil for the IRB model at the initialization, in 2010, and in 2020.

Historic:

The average annual total phosphorus loading from this simulation is 918,665 lbs. This simulation was initialized using default values of soil phosphorus and nitrogen. When initializing this same simulation with the soil phosphorus and nitrogen values after 21 years of poultry waste land application ("Soil Soluble P in 2020") the average annual total phosphorus loading increases to 1,611,706 lbs. This is a 57% average annual increase contributing to the loading in the rivers and streams coming only from the amount of phosphorus in the soil (that is, legacy phosphorus).

QUESTION 3

- Approximately what percent of the phosphorus loading through the rivers and streams into Lake Tenkiller is coming from point sources and what percent is coming from nonpoint sources?

There is approximately 3.46% of the total phosphorus loading through river and streams into Lake Tenkiller coming from point sources and 96.54% coming from nonpoint sources.

²² The subbasin that had a lower soluble phosphorus value in 2020 than it did in 2010 was subbasin 9. This is a result of good soil in that subbasin. This subbasin is producing a lot of biomass and there is less erosion happening. Since a constant stocking rate was used across the entire watershed, the amount of biomass left over at harvest, in this subbasin, is enough to pull some of the soluble phosphorus out of the soil which is why there is a reduction in 2020. Also, there is more precipitation in the eastern side of the watershed, which also contributes to more plant growth. This demonstrates the high resolution of inputs and the sensitivity of the model.

The model simulates an annual average of 36,708 lbs of total phosphorus loading into the rivers and streams from point sources. This data comes from the NPDES data from 2019 and is provided as a constant daily average value.

The annual average total phosphorus loading from the landscape is 1,023,292 lbs with 845,903 lbs coming from pasture land.

When the loading from the land and from point sources reaches the streams and river, there are a few biological processes that take place like algae growing and deposition of sediment in the river which can bury phosphorus resulting in a reduction in the total loading of phosphorus into the river. The instream nutrient modification from our model is 12.78% reduction.

In addition, there are also chemical changes from organic to soluble phosphorus, which account for roughly an additional 0.5535% reduction of total phosphorus reaching the waterways.

So there is a total reduction of 13.3335% in the total phosphorus loading from the landscape that reaches the waterways.

The annual total phosphorus loading from point sources reaching the lake is:

$$36,708 \text{ lbs} - (36,708 * 0.133335) = 31,813.54 \text{ lbs}$$

The annual total phosphorus loading from nonpoint sources reaching the lake is:

$$1,023,292 \text{ lbs} - (1,023,292 * 0.133335) = 886,851.4 \text{ lbs}$$

This results in a total annual total phosphorus load reaching the lake of about 918,665 lbs.

The percent of this loading from the point sources reaching the lake is:

$$(31,813.54 \text{ lbs} / 918,665 \text{ lbs}) * 100\% = 3.46\%$$

The percent of this loading from nonpoint sources reaching the lake is:

$$(886,851.4 \text{ lbs} / 918,665 \text{ lbs}) * 100\% = 96.54\%$$

Thus, 3.46% of the total phosphorus load is from point sources and 96.54% of the total phosphorus load is from nonpoint sources.

QUESTION 4

4. Assuming all land application of poultry waste in the IRW ceased in 2010, would legacy phosphorus from pre-2010 poultry waste land applications still be a substantial contributor to phosphorus loading in the IRW in the future?

Yes, legacy phosphorus is currently a substantial contributor to total phosphorus loading into the river and will continue to be a substantial contributor of total phosphorus loading into the river in the IRB in the future.

Legacy phosphorus is the amount of phosphorus that is left in the soil at the end of the year. Looking at the change in phosphorus in the soil can show the impact of legacy phosphorus in the watershed.

Initializing the model with soil phosphorus and nitrogen values found as representative of the model in 2010 (10 years with poultry waste land application), ceasing all future poultry waste application in the

watershed, and using the same management shows a decrease in total phosphorus in the soil of an average of 1.7 lbs/acre per year based on a 20-year simulation.

Total phosphorus in the soil has two components, organic phosphorus and soluble phosphorus. Soluble phosphorus is equivalent to the soil test phosphorus (STP) field measurements. So, soluble phosphorus is the critical component of total phosphorus when looking at overall soil health. Even though there was a decrease in total phosphorus in the soil during the 21-year simulation, the watershed average of soluble phosphorus in the soil increased ~0.8 lbs/ac and organic phosphorus in the soil decreased ~2.5 lbs/ac. So, the decrease in the soil is driven by the decrease in organic phosphorus. Organic phosphorus in the soil is decreased when it is converted into soluble phosphorus and organic phosphorus can also attach to sediment and be removed from the soil.

Starting the model in 2010 and simulating a cessation of poultry waste land application shows the soluble phosphorus is no longer drastically increasing year over year. However, there still is an increase in soluble phosphorus year over year.

Annual Change of Phosphorus in Soil with Litter Removed starting in 2010

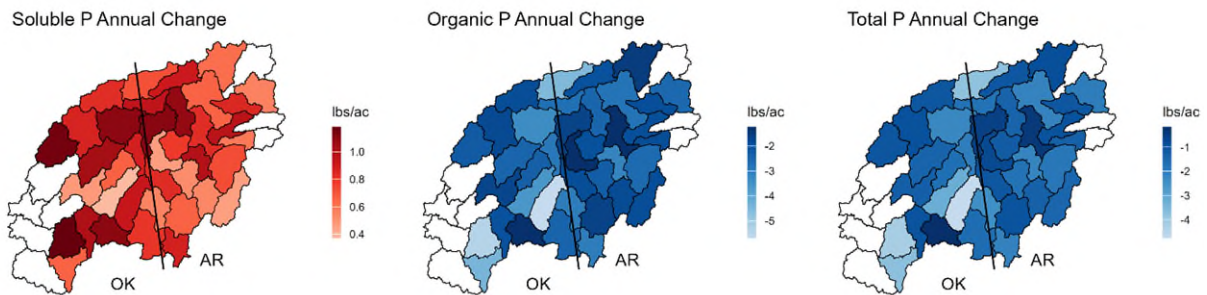


Figure 22. Annual change in phosphorus in the soil in pasture land with cessation of poultry waste land application starting in 2010. White subbasins did not previously receive poultry waste land application.

For example, in subbasin 25, there is still an increase in soluble phosphorus of about 1.15 lbs/ac or about 0.575 ppm annually over the 21-year simulation. This shows that simply ceasing poultry waste land application will not reduce the amount of soluble phosphorus in the soil.

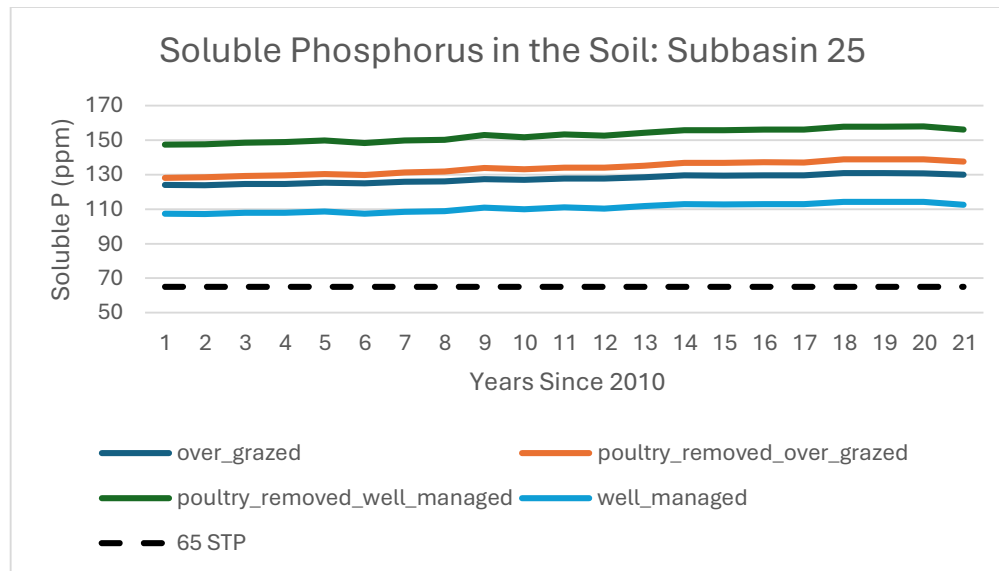


Figure 23. Soluble Phosphorus (P) in the soil in Subbasin 25 for 4 different management practices with the cessation of poultry waste land application starting in 2010. The 65 STP goal is marked with a black dashed line.

QUESTION 5

5. Using the SWAT model, and assuming a cessation of poultry waste land application practices in the Illinois River Watershed (but no other changes) in 2010, would phosphorus from historic poultry waste land application continue to contribute to exceedances of the .037mg/l water quality standard in the rivers and streams of the Illinois River Watershed in Oklahoma?

Yes, if there was a cessation of poultry waste land application in the IRB, the historic application of poultry waste would still contribute to the exceedance of the 0.037mg/l water quality standard in the rivers and streams in the IRW in Oklahoma.

The concentration of phosphorus into the waterways does show a slight reduction in the subbasins where poultry waste is no longer applied. However, the concentration of total phosphorus at the outlet doesn't reflect this change. In fact, there is a slight increase over the simulation even with the cessation of poultry waste land application over the 21-year simulation. The increase in concentration toward the outlet of the watershed is due to the increased amount of total phosphorus loading from the legacy phosphorus in the soil. So simply ceasing to apply poultry waste will not be enough to reduce the concentration of total phosphorus below the OK water quality standard.

The total phosphorus concentrations in the last year of the 21-year simulation of cessation of poultry waste land application starting in 2010 is 0.032 mg/l in subbasin 45 in OK where there is very little poultry production activity. This demonstrates the ability of the model to reflect the sensitivity of the range of poultry production activities. The overall watershed annual average concentration of total phosphorus is 0.22 mg/l which is ~600% over the water quality standard. Below is a map of the final concentration averaged over each subbasin in the IRB for the last year of the 21-year simulation. All subbasins are above the 0.037 mg/l standard except for subbasin 45 in OK.

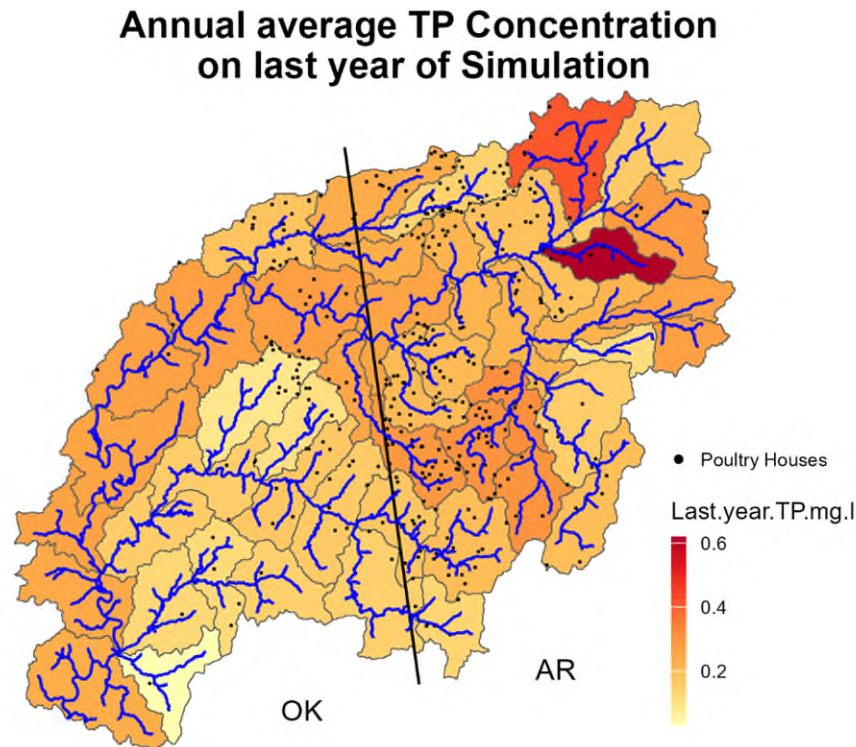


Figure 24. Annual average Total Phosphorus (TP) concentration in the last year of a 21-year simulation of cessation of poultry waste land application.

QUESTION 6

6. What can the SWAT model tell us about whether there exist land management techniques that could help reduce phosphorus loading from historic and current poultry waste land application practices in the Illinois River Watershed?

The model shows that there do exist land management techniques that can help reduce total phosphorus loading from historic and current poultry waste land application practices in the IRB.

The model can implement reduction strategies spatially across the watershed and analyze the impacts on loading into the rivers and water quality. Additional land management techniques the model is capable of simulating include land use changes such as cessation of poultry waste land application, the addition of wetland areas, change in cattle grazing practices, and what is planted in a field or pasture.

To demonstrate land management techniques that could help reduce the phosphorus loading in the IRB, a few scenarios were selected. To get the closest to current conditions as possible, the model was set with 2020 (21 years of poultry waste application) soil phosphorus values to see reductions that start with more realistic soil phosphorus levels.

The first scenario simulated was no change in management across the watershed. This was done to show how the current modeled practices would impact the loading if nothing was done. The next scenario was to cease poultry waste application but maintain all other practices in the watershed. The next scenario was to cease poultry waste application and simulate hay production on the pastures that

were previously receiving poultry waste and were overgrazed (~4% of pasture land). The final scenario was to cease poultry waste application and apply a 15m (~49 foot) filter strip on all pasture land in the watershed.

The following table shows the annual average loading from a 21-year simulation for each of the scenarios. The corresponding percent of reduction from the “No Change to Management” scenario is shown.

When simulating no additional application of poultry waste starting in 2020, the overall loading of total phosphorus into the rivers and reaching Lake Tenkiller will reduce on average 5.6% a year. If 4% of the over grazed pastures have no additional poultry waste application and are used for hay production, the decrease of total phosphorus loading is 9.6% annually on average. When 15m (~49 foot) filter strips are applied on all pasture land coupled with the cessation of poultry waste land application, then the loading into the rivers and lake has an average annual decrease of 62%. In order to reduce the amount of loading that reaches the rivers and lake, additional management practices are needed beyond the cessation of poultry waste land application.

Table 18. Annual average Total Phosphorus (TP) loading and the percent of reduction for various land management techniques.

	Total Phosphorus (lbs)	% Reduction of Total Phosphorus
No Changes to Management	1,611,706	
No Litter (same grazing)	1,521,608	5.6%
No Litter, Hay Production on 4% of Pasture	1,457,345	9.6%
No Litter and 15m Filter Strip All Pasture	612,723	62.0%

With any best management practice (BMP), maintenance is required. A filter strip left unmaintained, or maintained poorly, can move from an area of sink where total phosphorus is stored, to an area of source. Once the filter strips become saturated with total phosphorus they can become a significant source of contribution to the waterways. Additionally, enhanced poultry information exchange, more robust monitoring of soil phosphorus, and water quality sampling at all flow conditions are required to assess and enhance the effectiveness of the BMPs.

QUESTION 7

- Using the SWAT model, what effects on phosphorus loading / phosphorus concentrations would these various land management techniques have?

When simulating no additional application of poultry waste starting in 2020, the overall concentration of total phosphorus in the river reaching Lake Tenkiller will reduce in concentration by 0.017 mg/l or ~90,100 lbs. When an additional land management technique of adding a ~49 foot (15 meter) filter strip on the edge of all pasture fields across the entire watershed, the model simulates an average reduction of 0.2 mg/l or ~1,000,000 lbs. Simulating hay production on the 4% of land that previously had poultry waste applied and was over grazed, results in a 0.03 mg/l or ~154,361 lbs average annual reduction. This shows that simply ceasing poultry waste application is not sufficient to reduce the concentration of total phosphorus in the river.

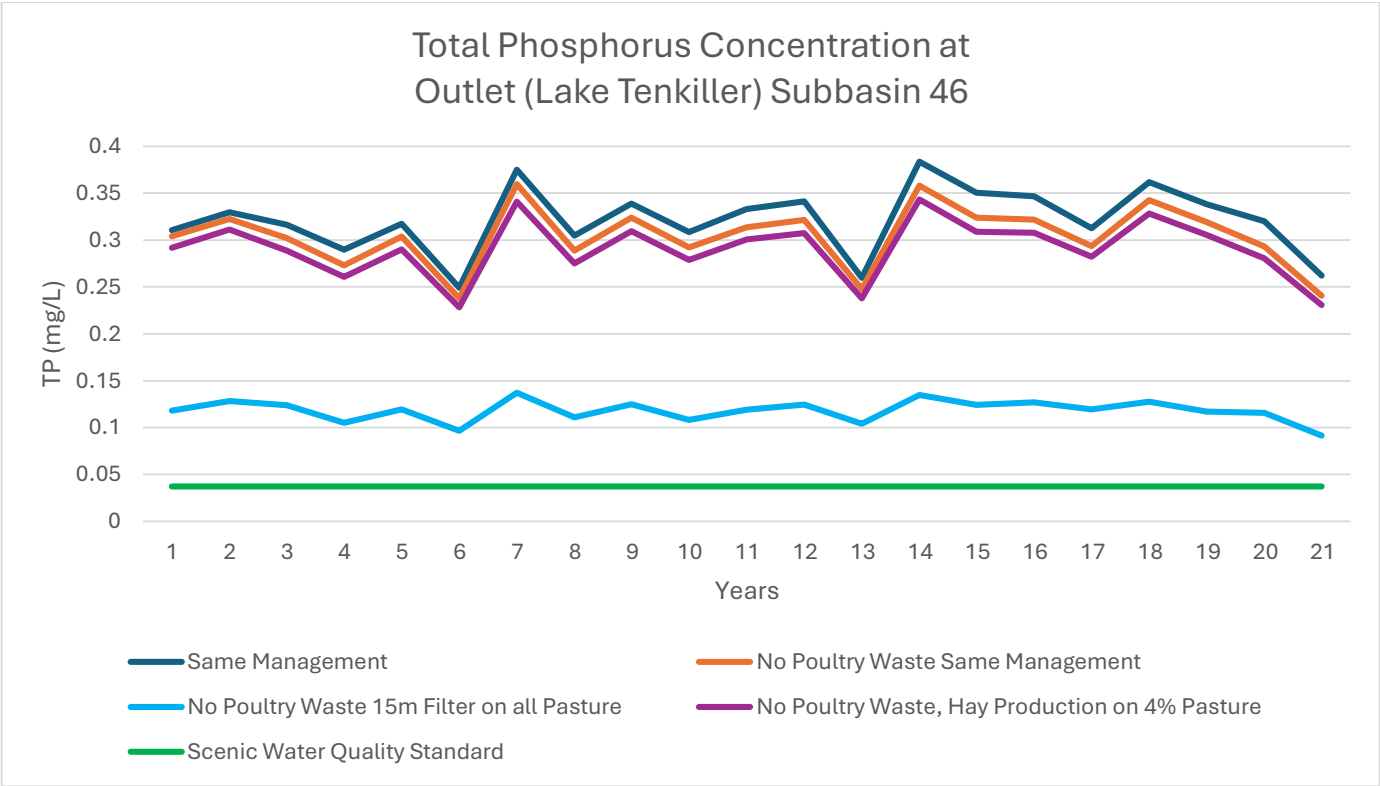


Figure 25. Change in the Total Phosphorus (TP) concentration over time at the outlet (Lake Tenkiller) of the IRB watershed.

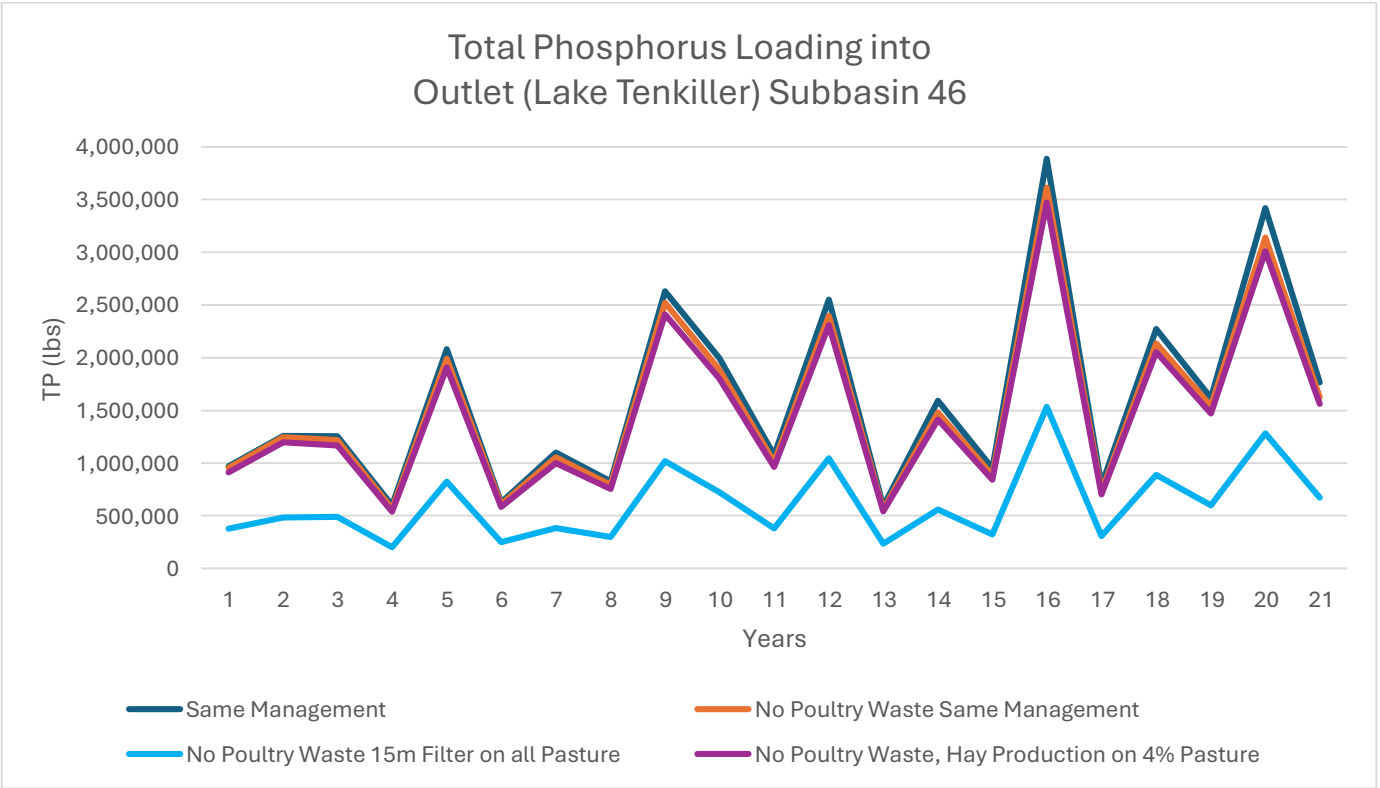


Figure 26. Change in the Total Phosphorus (TP) loading over time at the outlet (Lake Tenkiller) of the IRB watershed.

In addition to concentration and loading of phosphorus in the water, the amount of phosphorus in the soil is also important when understanding the effects of BMPs in the watershed. For the scenario with no changes to the management, the soluble phosphorus levels in the soil remain constant with grazing management with no poultry waste applied and increase where poultry waste is applied.

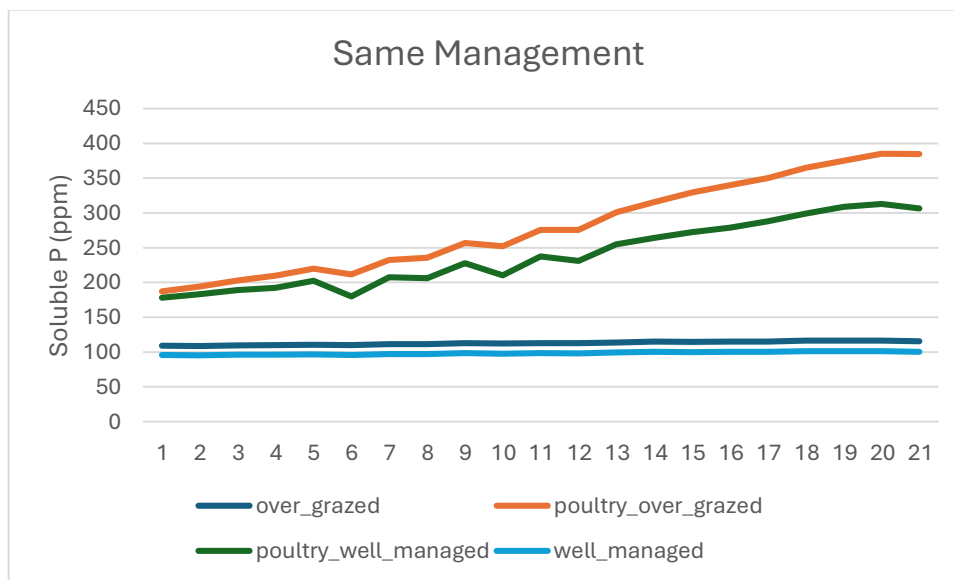


Figure 27. Soluble Phosphorus (P) in the soil (initialized in 2020) averaged over the pasture land with 4 different management practices with no change in management practices.

When poultry waste is no longer applied, and when no poultry waste is applied and the 15m filter strip is applied to all pasture land, the soluble phosphorus levels are equivalent between the two scenarios and remain the same in the soil.

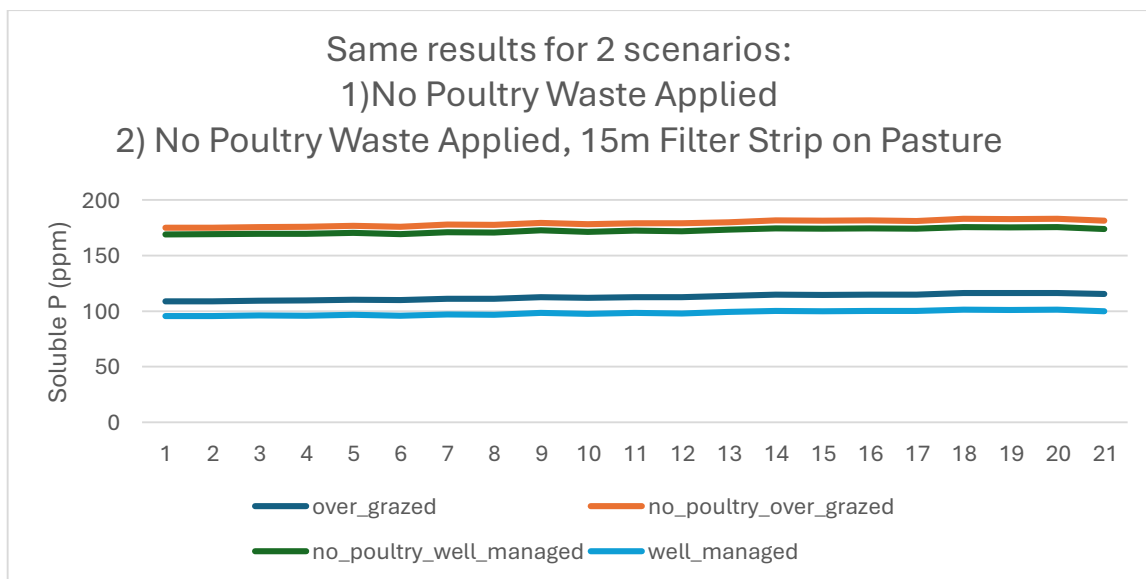


Figure 28. Soluble Phosphorus (P) in the soil (initialized in 2020) averaged over the pasture land with 4 different management practices with cessation of poultry waste, and 15m filter strips on all pasture land.

One way to remove the phosphorus in the soil is to grow the bermudagrass on the field and harvest it to feed the animals, but not have any animals graze on the pasture. Removing cattle from the same location that received poultry and was over grazed (~4% of the pasture land) and harvesting the grass

results in a reduction of ~12 ppm over a 21 year simulation. At this rate of 0.57 ppm a year, it would take 184 years to bring those fields down to the 65 STP goal.

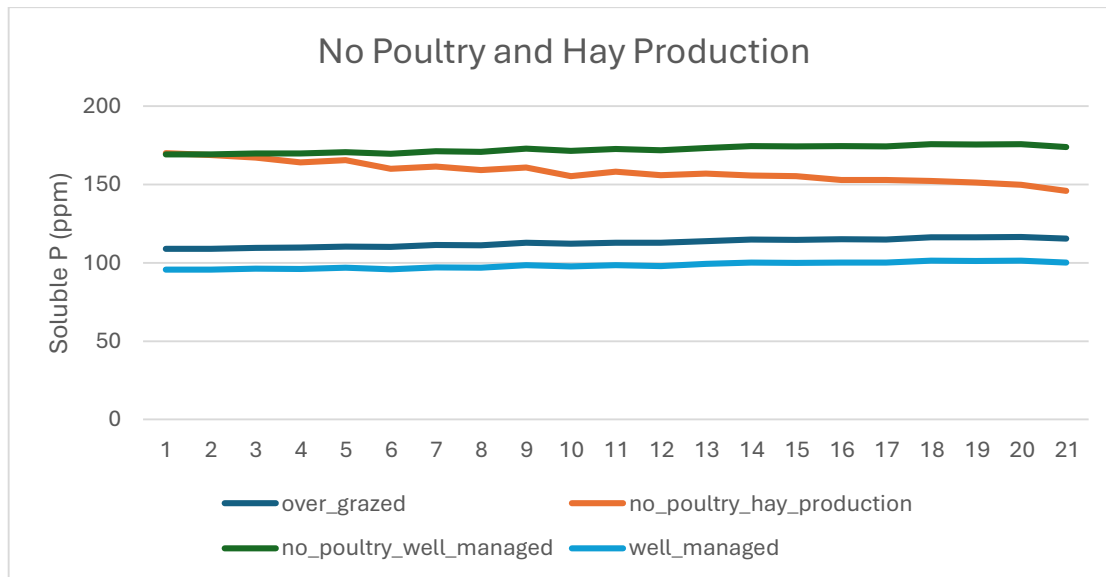


Figure 29. Soluble Phosphorus (P) in the soil (initialized in 2020) averaged over the pasture land with 4 different management practices with cessation of poultry waste and hay production on 4% of previously over grazed pasture land.

QUESTION 8

8. Do you have any critiques of the Arkansas SWAT model (the UIRW model), and if so, what are they?

In my opinion, there are many problems with the UIRW model, including input data used and methods used for calibration.

- The UIRW model did not model the exact same areas or have the same subbasin delineation. The IRB (TX A&M) model used about 60% more HRUs than the UIRW model (6,906 compared to 2,515) and included about 135,000 more acres. The IRB model included an average of 142 acres per HRU and UIRW model included an average of 337 acres per HRU. Using more HRUs across the watershed allows a model to simulate management in a more spatially precise manner.
- There were differences in land use classification between the two models. UIRW model grouped land use into only three classes, Forest (44%), Hay (44.5%) and Urban (11.5%). The IRB model in contrast used 22 unique land use classifications. This caused significant differences in the acreage for some classes, particularly urban class. The UIRW model, in fact, estimated significantly more urban area in both states than the IRB model, which was due to the classification of roadways across the watershed as Urban. This defining of roadways as unique HRUs within the model resulted in an over estimation of the total amount of urban land in the watershed in the UIRW model. The IRB model grouped the roads across the watershed into the land use class that the road passed through or along.
- There were also differences in the precipitation data between the two models because although both used PRISM data, the UIRW model used data from 1990-2020 while the IRB model used the PRISM data from 2000-2020. Since 2000, the precipitation patterns in the watershed have

significant changed from the 1990-2000 period. The UIRW model thus simulated less precipitation on average for the watershed, which could cause bias and uncertainty in the UIRW model.

- Point sources used from the UIRW model accounted for an average of ~417,600 lbs/yr of phosphorus from 2000-2020. The IRB model in contrast used 36,700 lbs/yr based on NPDES point source permits from 2019. The IRB model phosphorus point source loading more accurately reflects what has been reported since 2007. The UIRW model point source values are not representative of what has been reported since 2007 in the NPDES database.
- The UIRW model input soluble phosphorus values into the soil based off Storm et al 2006 values from early 1990s (1991-1995) but it used a value of 0.01 for organic phosphorus and did not put in any initial values for nitrogen. Not accurately initializing the soil with both components of phosphorus and nitrogen can cause discrepancies and uncertainty in the biomass estimation in the model which makes the water quality prediction of the model unreliable.
- The UIRW model varied calibration values in subbasins with gages to achieve calibration and then used different values in subbasins upstream or between gages. This method does not treat the watershed or channel as a complete system and does not accurately reflect the physical processes within the watershed. The IRB model in contrast set calibration values for the entire watershed, which simulates more realistic physical processes across the watershed. Also, some of the UIRW model calibration values are outside acceptable ranges for the region. For example, the UIRW model used ESCO and ALPHA_BF values that exceeded acceptable ranges.
- The IRB model used a more extensive list of parameters for sediment, nitrogen, & phosphorus calibration which provides a more robust calibration of the model. The UIRW model varied the water quality calibration values in subbasin with gages to achieve calibration, then used different values in subbasins upstream or between gages. This approach does not accurately reflect the physical processes within the watershed. The UIRW model put a significant amount of nitrogen & phosphorus directly into the channel, which bypasses physical/land use processes that the model accounts for within the watershed. The UIRW model was calibrated against observations, it only looked at the day of the observation, not a continuous calibration (not every flow condition (low/high)). The IRB model used LOADEST to generate continuous time series to capture all flow conditions for calibration.
- There were significant differences in how the models accounted for poultry waste effects, which included nitrogen species, poultry waste nutrient content, types of land and areas that poultry waste was applied, and application rates. The UIRW model applied poultry waste at rates ranging from 0.03 to 1.9 ton/acre. OCC stated that most machinery used to apply poultry waste cannot apply at rates less than 0.5 ton/acre. Additionally, the nutrient content of the poultry waste in the UIRW model was much higher than the IRB model and speciated differently.
- Methods to estimate poultry waste produced and therefore applied in the watershed varied significantly. The UIRW model estimated a much smaller number of birds produced in the watershed. It simulated 522 houses with each house producing an average of 23,000 birds per year. The IRB model estimated a larger number of active houses (1,345) with an average of 129,000 birds per year. The amount of poultry waste produced in the IRB model was only 32% as much poultry waste produced per year as the UIRW model. (The IRB model estimated approximately 141 tons per year per house and UIRW model estimated approximately 1529 tons per year per house). The IRB model estimated approx. 50% (127,985 tons) of poultry waste being transported outside the watershed each year. The UIRW model estimated the removal of 814,631 tons of poultry waste per year, which the OCC states is unrealistic.

- The two models differed in their grazing simulations in terms of differentiation between management, manure production, rest cycles, and manure production. The UIRW model simulated a manure rate of 40 lbs/ac/day, which would require cattle to eat more than that 60-70 lbs/day, so the pasture would need to produce ~20 tons of grass to support cattle which is not possible. The manure produced from cattle is greater in the UIRW model, but the length of grazing is significantly less which would have a significant impact on the amount of sediment loading into the rivers.
- There were differences in how hog farms were simulated between the two models. The UIRW model did not include the same hog farms that were provided to us from FTN (original source AR DEQ Permitted Data System (PDS)). In addition, there was an error in the nutrient ratios of manure for one farm. However, hog manure application is such a small portion of the watershed, this likely did not impact the models significantly.
- Similarly, there are dairy farms missing from the UIRW model that were included in the information provided to us from FTN (original source AR DEQ Permitted Data System (PDS)), along with errors in nutrient ratios for one farm. But again, as dairy manure affects so few areas of the watershed, it did not likely have a large impact on the models.
- Comparing sediment data loading maps between the two models, the IRB model links sediment loading from the management in the watershed most closely to areas of overgrazed pasture. It is less clear what the source of sediment loading is for the UIRW model. This could be from the sediment variables it varied across basins for sediment calibration.
- Total phosphorus loading in the IRB model is most closely related to the watersheds with larger numbers of poultry houses where the 50% of the poultry waste was applied. The UIRW model has no clear indication of where the phosphorus loading is coming from except perhaps during calibration where it added phosphorus directly into the river to achieve calibration.
- Nitrogen loading from some portions of the basin was much larger in the UIRW model than the IRB model, and although there was greater agreement on the areas of the basin contributing to nitrogen loading than phosphorus loading, there were still some significant differences. Differences in nitrogen contribution from urban areas may relate to differences in the amount of urban land estimated by the models. Also, the lack of organic nitrogen in poultry waste in the UIRW model could contribute to higher total nitrogen values.

Submitted: November 18, 2024



Katie Mendoza

APPENDIX A: MODEL SIMULATION OF STREAMFLOW COMPARED TO USGS GAGE STREAMFLOW

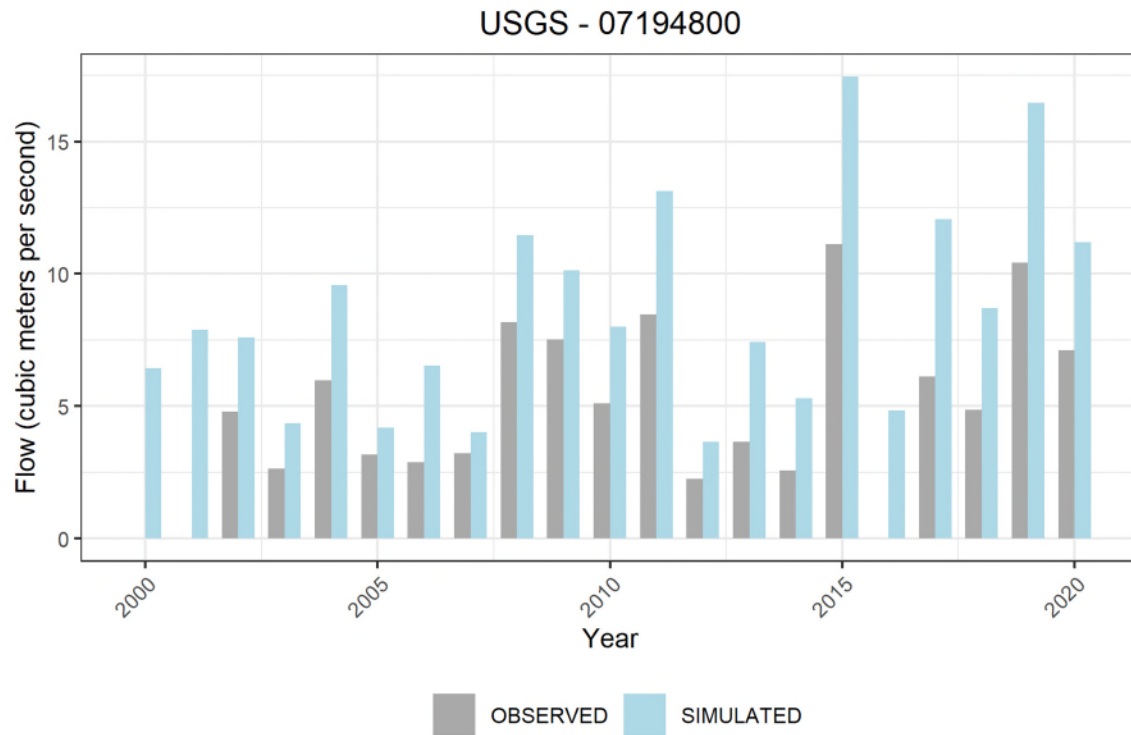


Figure 1. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07194800 and Subbasin 3.

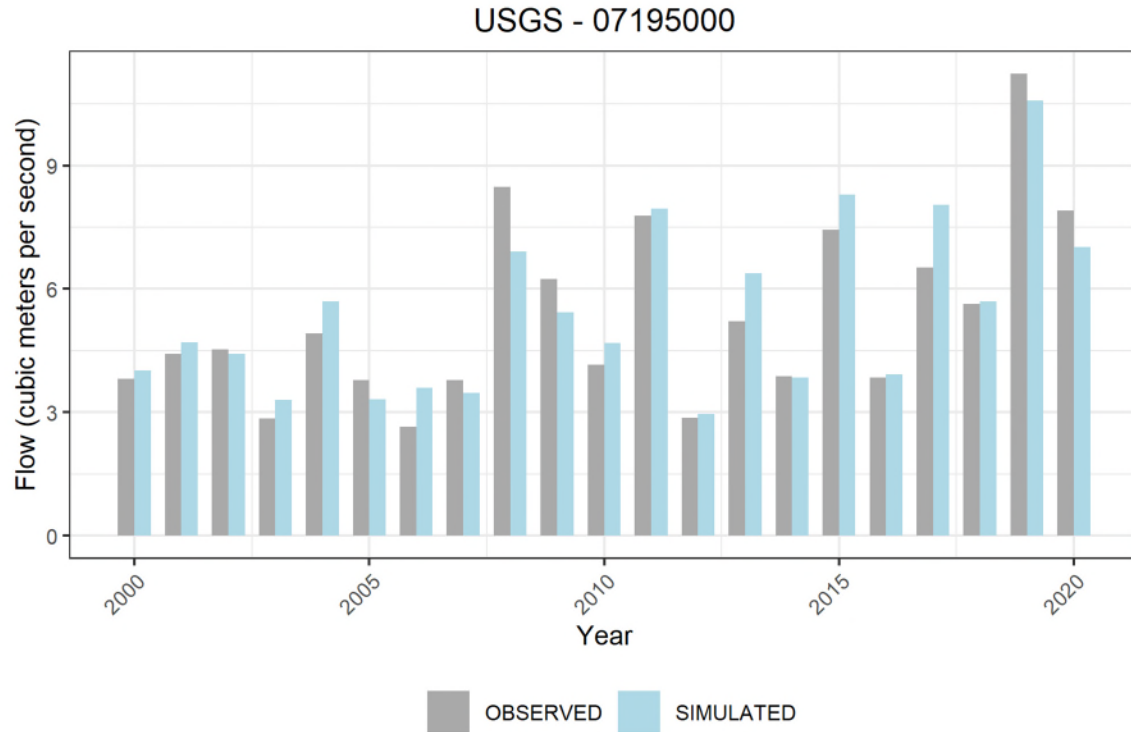


Figure 2. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07195000 and Subbasin 8.

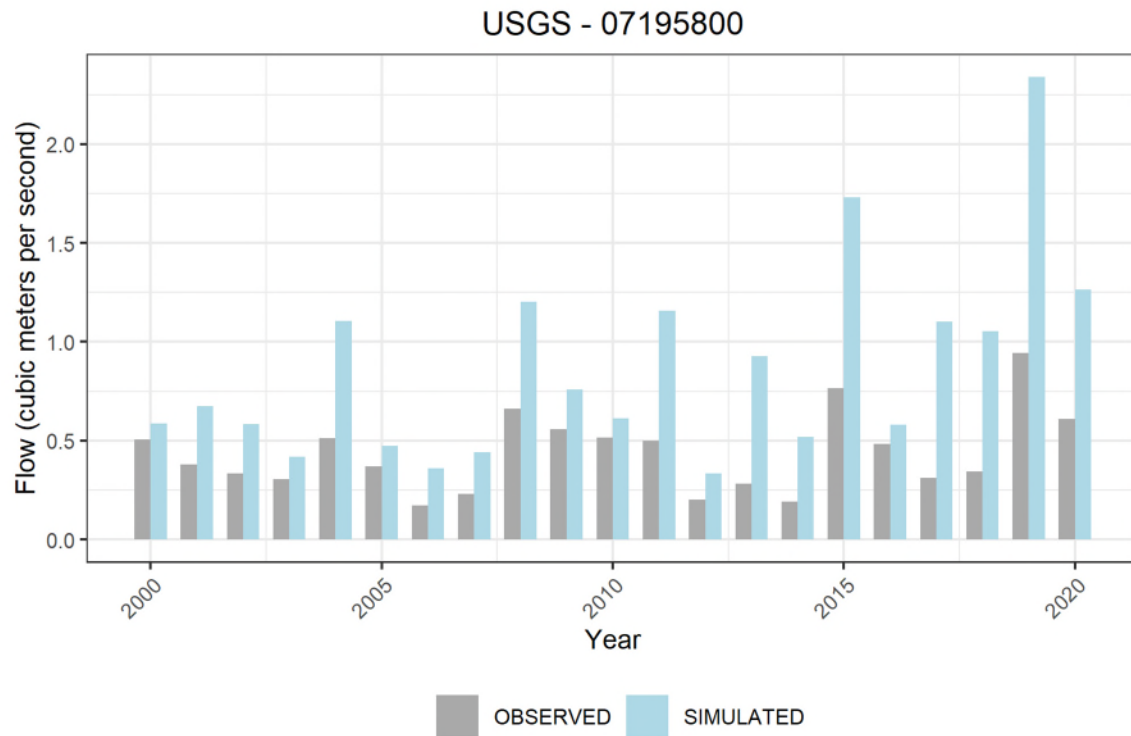


Figure 3. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07195800 and Subbasin 16.

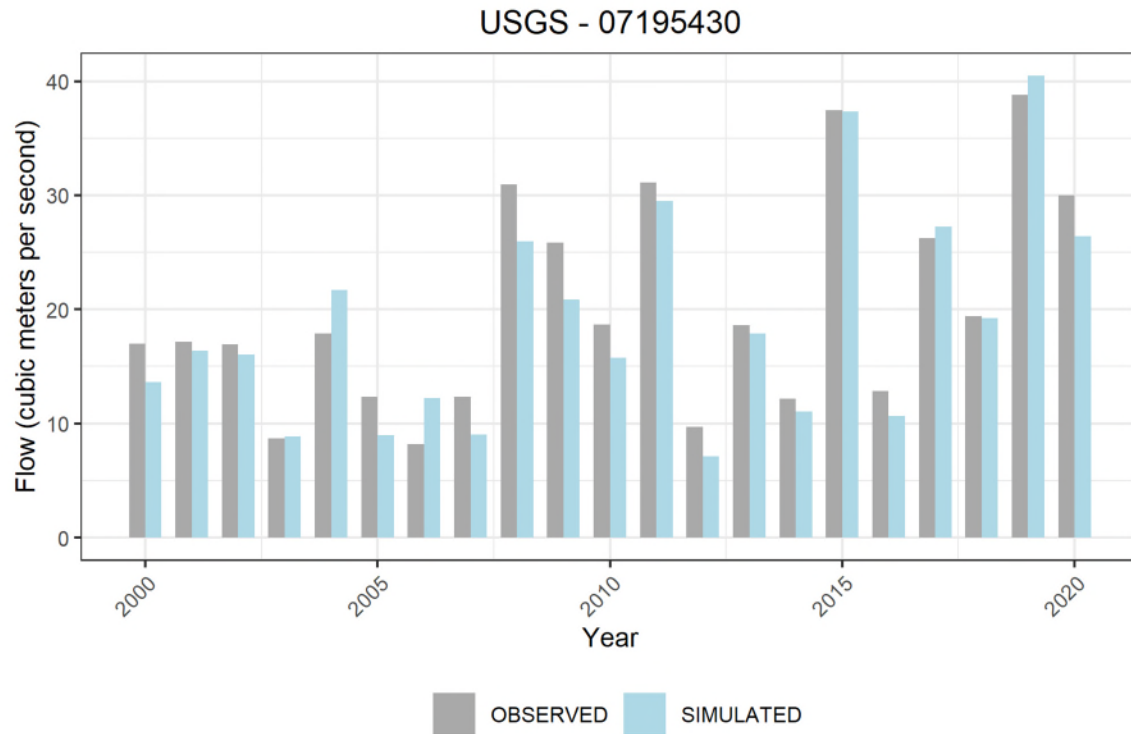


Figure 4. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07195430 and Subbasin 25.

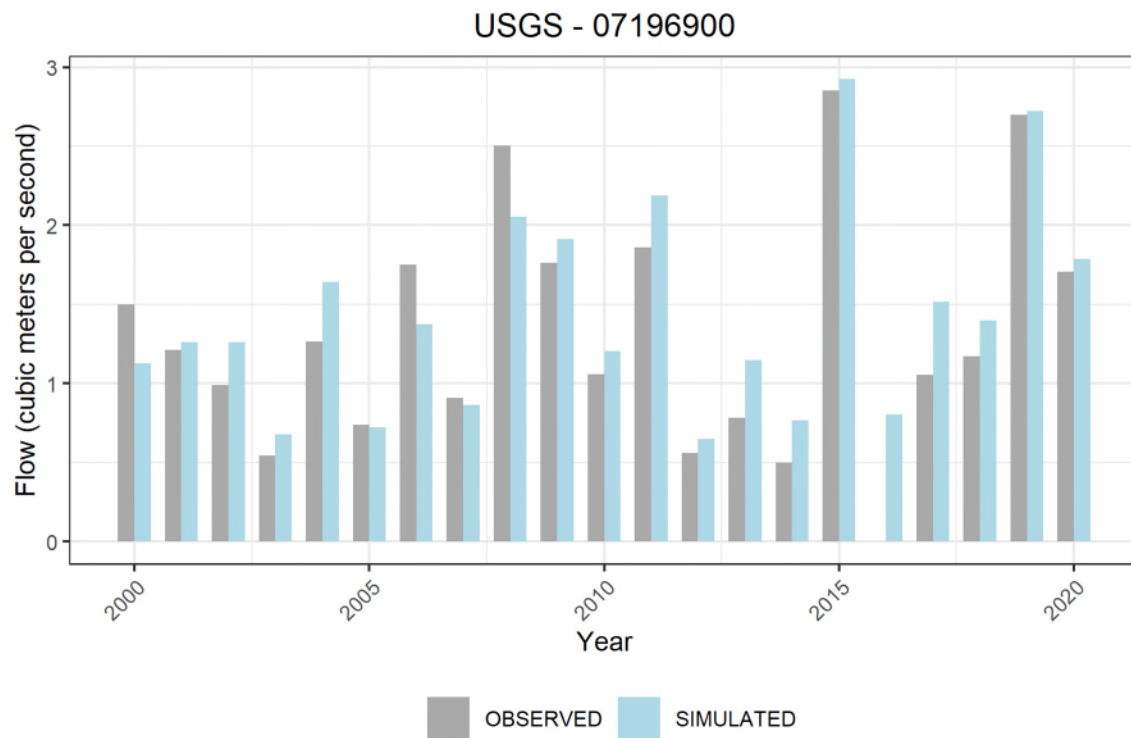


Figure 5. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07196900 and Subbasin 27.

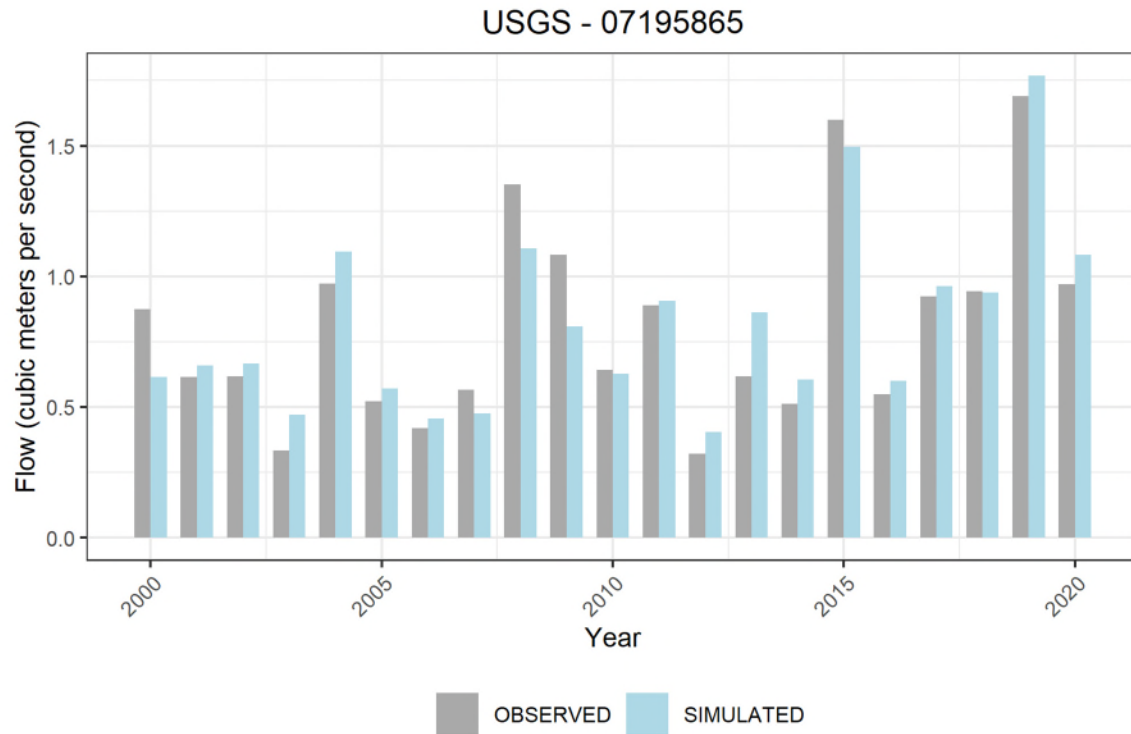


Figure 6. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07195865 and Subbasin 17.

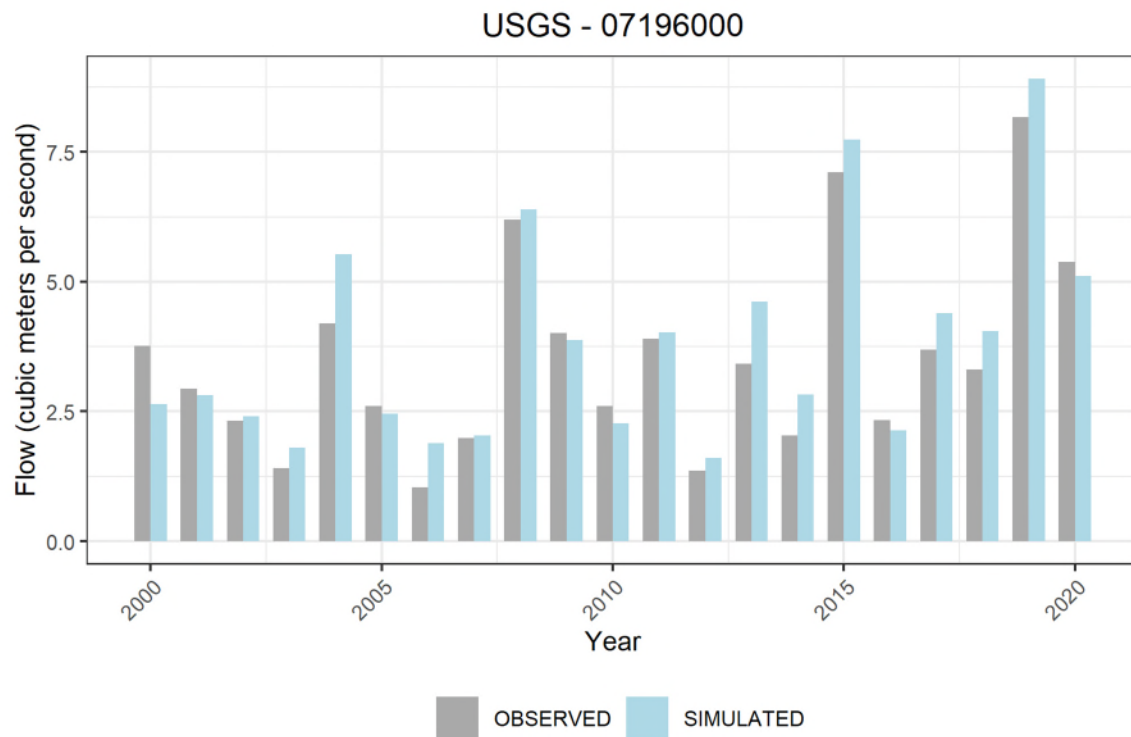


Figure 7. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07196500 and Subbasin 19.

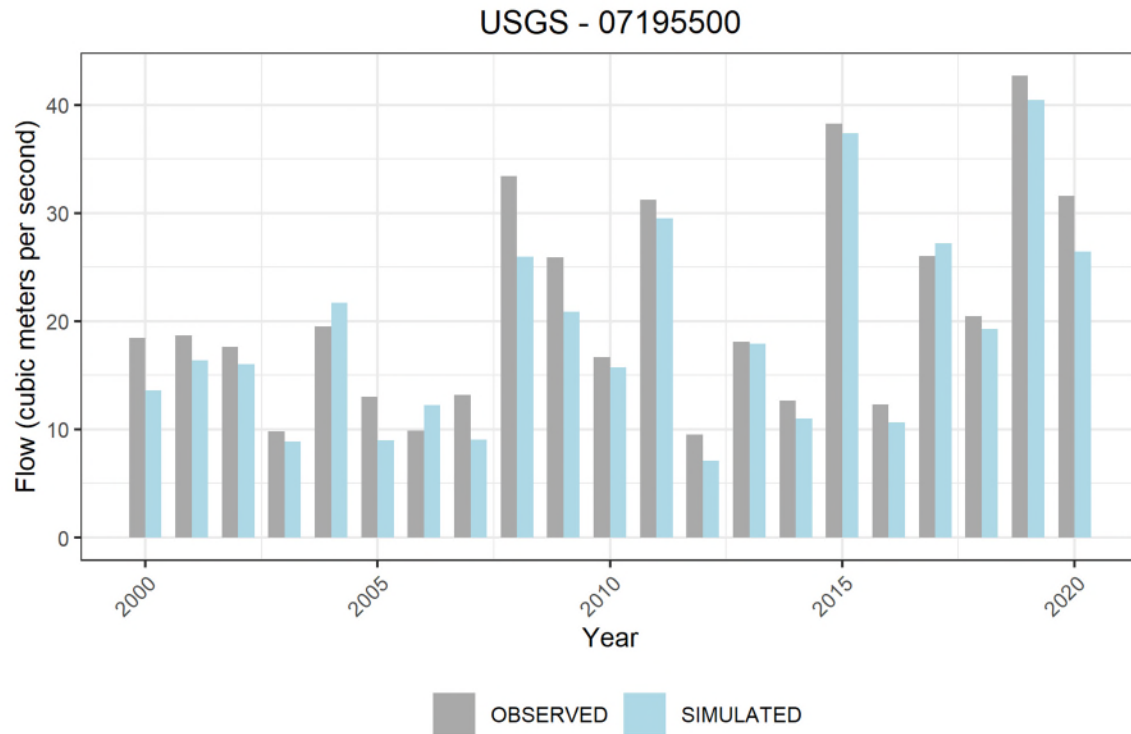


Figure 8. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07195500 and Subbasin 25.

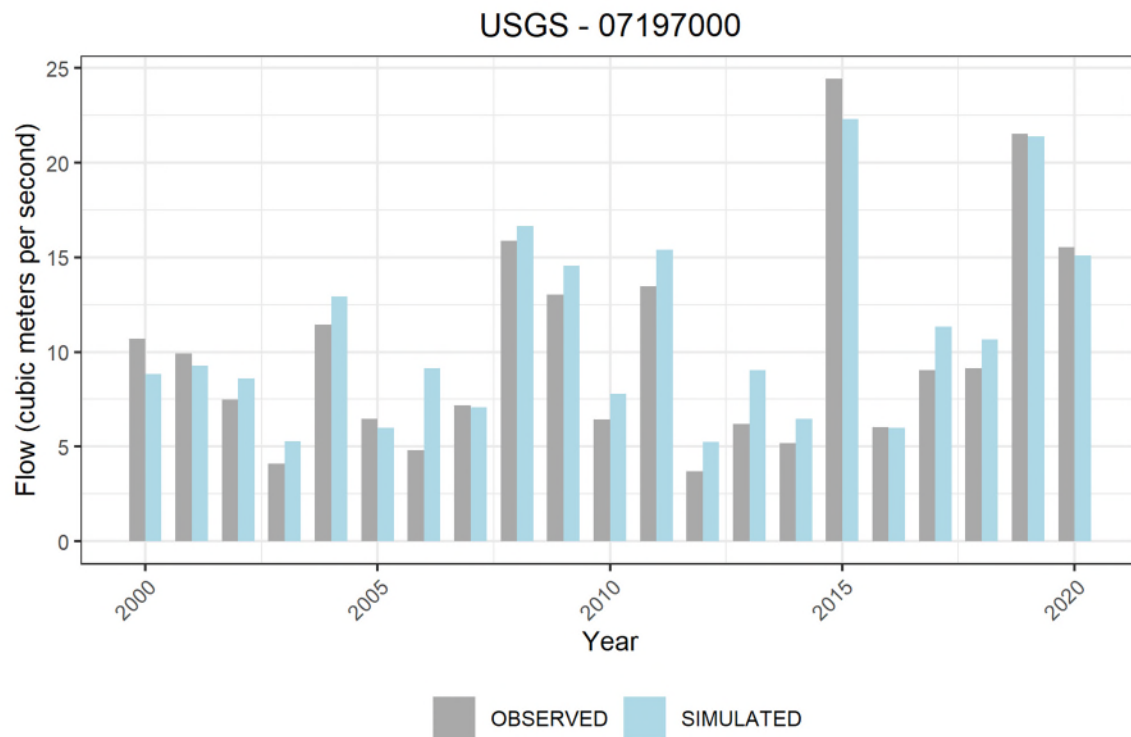


Figure 9. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07197000 and Subbasin 35.

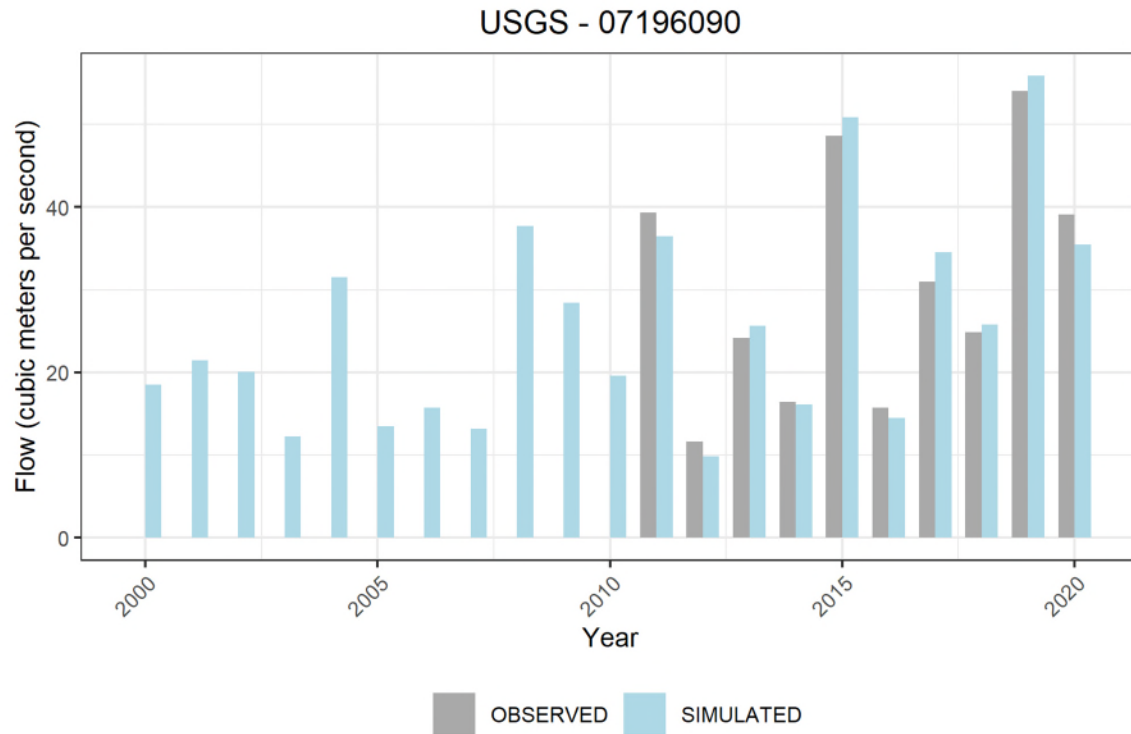


Figure 10. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07196090 and Subbasin 37.

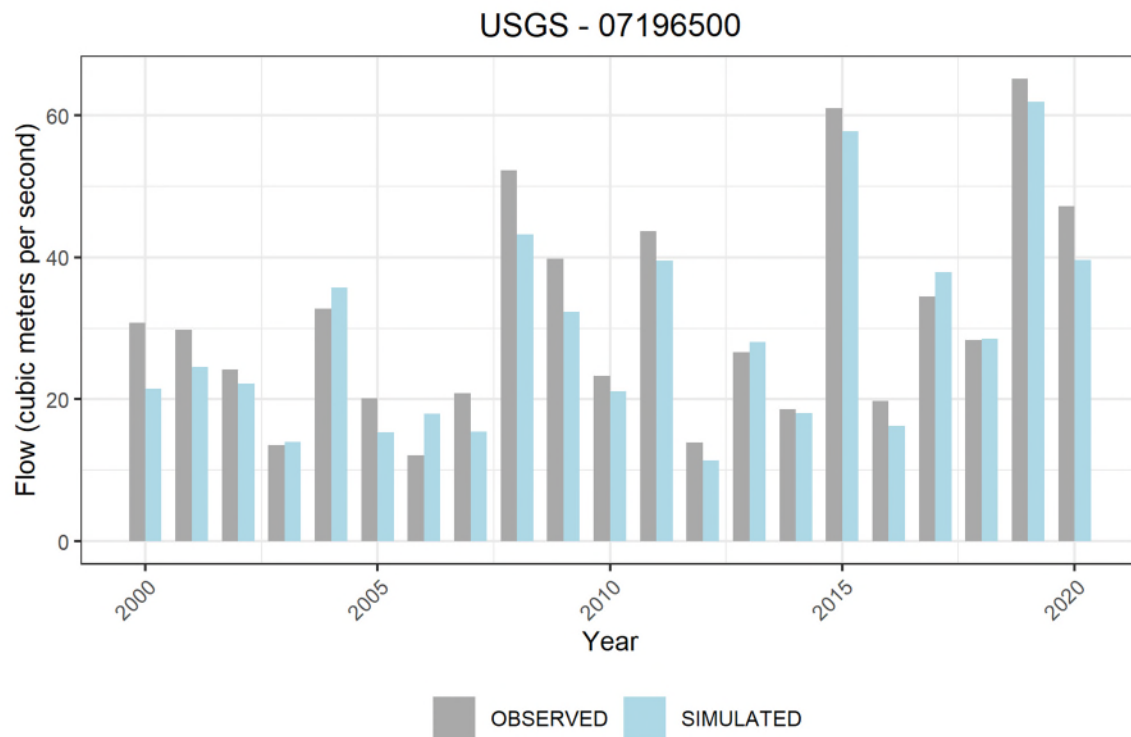


Figure 11. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07196500 and Subbasin 39.

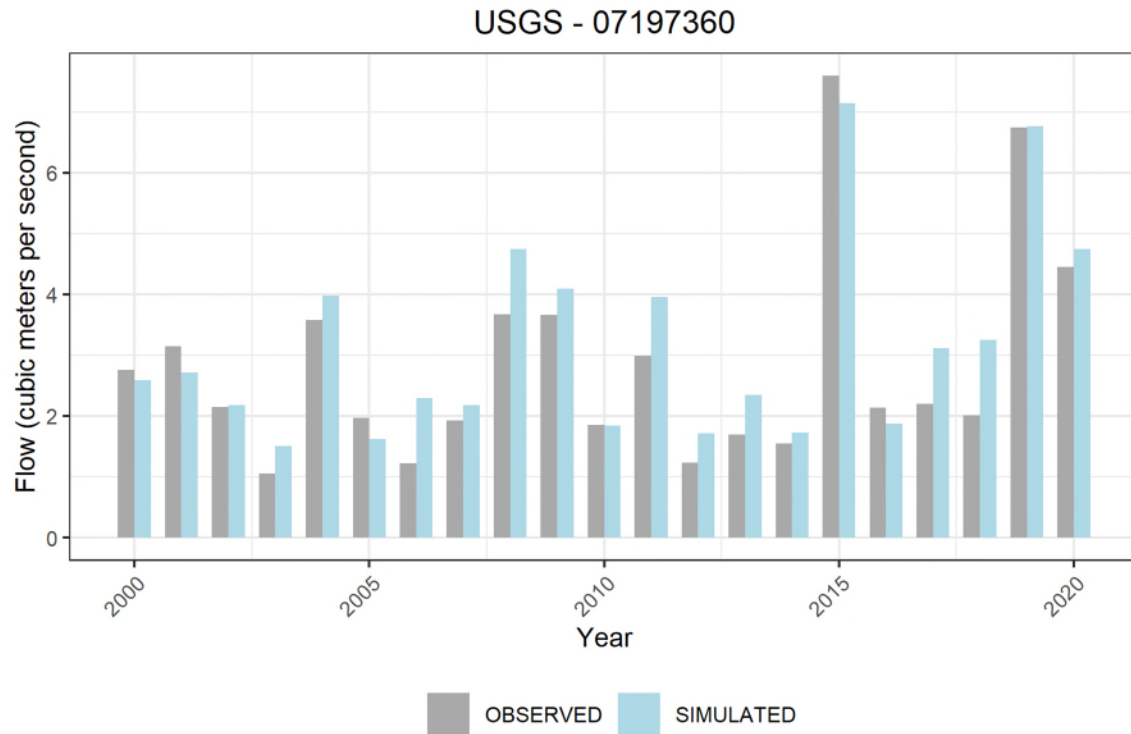


Figure 12. Comparison between the annually averaged USGS observations (grey) and SWAT simulated (blue) flow for USGS gage 07197360 and Subbasin 43.

APPENDIX B: MODEL SIMULATION OF TOTAL PHOSPHORUS LOADING IN THE WATERSHED COMPARED TO LOADEST INPUT GENERATED FROM GRAB SAMPLE OBSERVATIONS

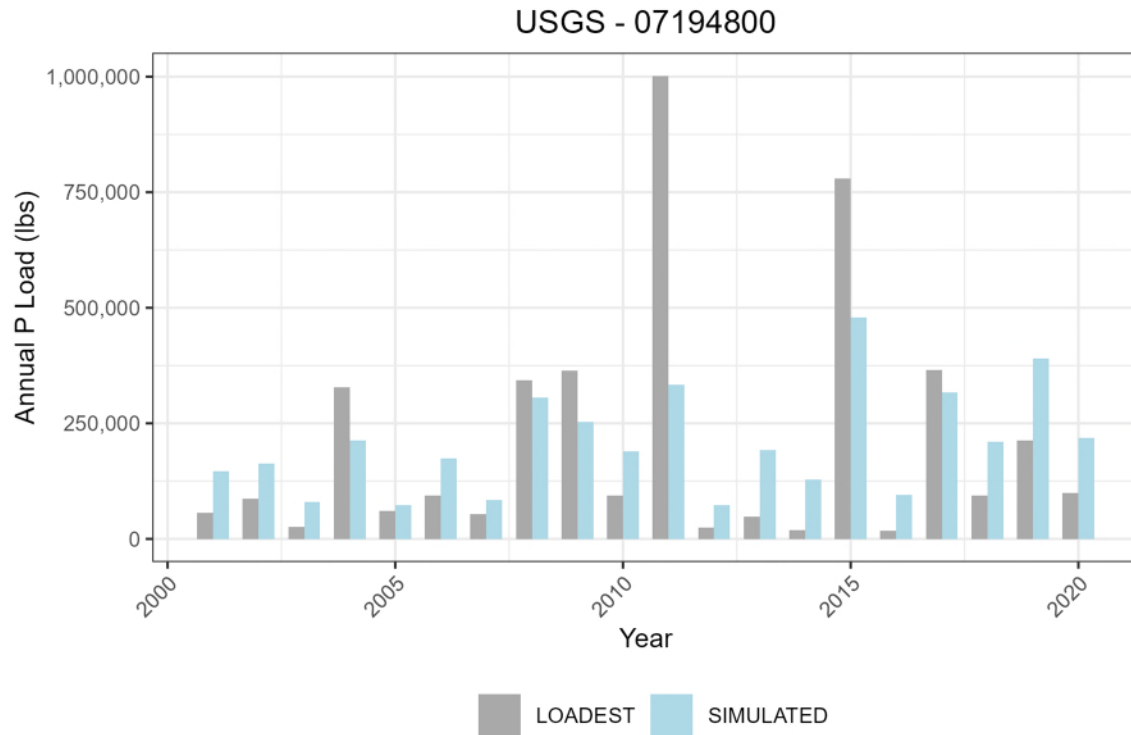


Figure 1. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07194800 and Subbasin 3.

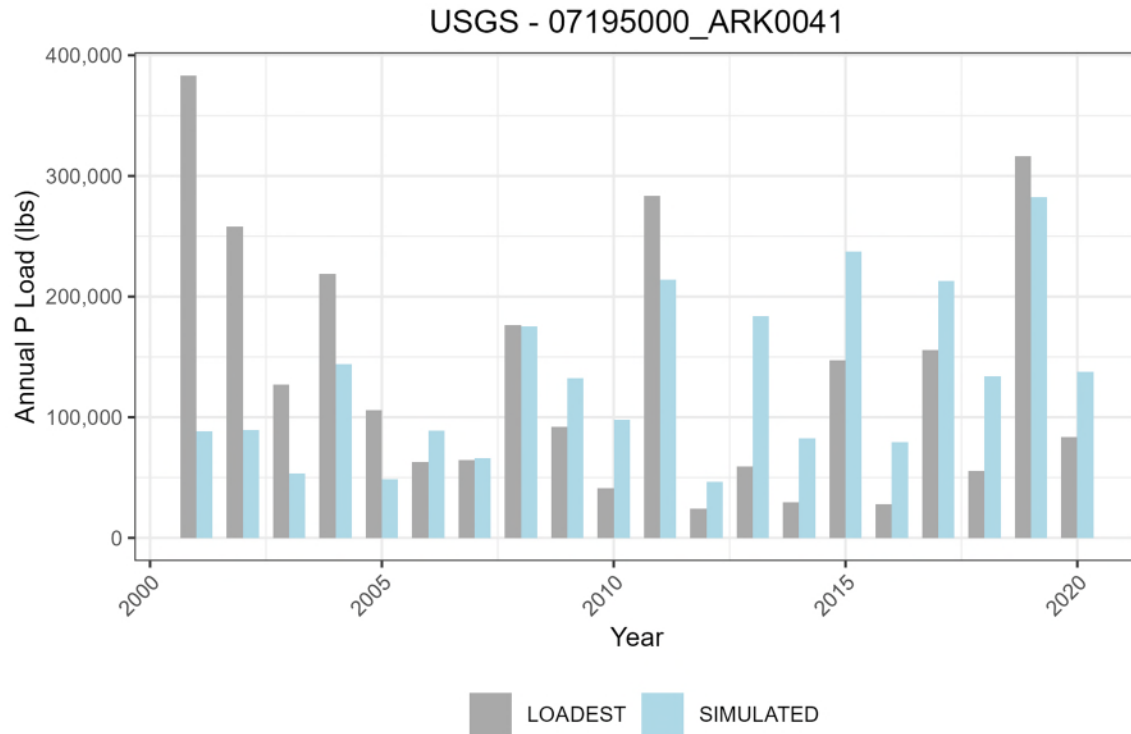


Figure 2. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07195000--AR-DEQ ARK0041 and Subbasin 8.

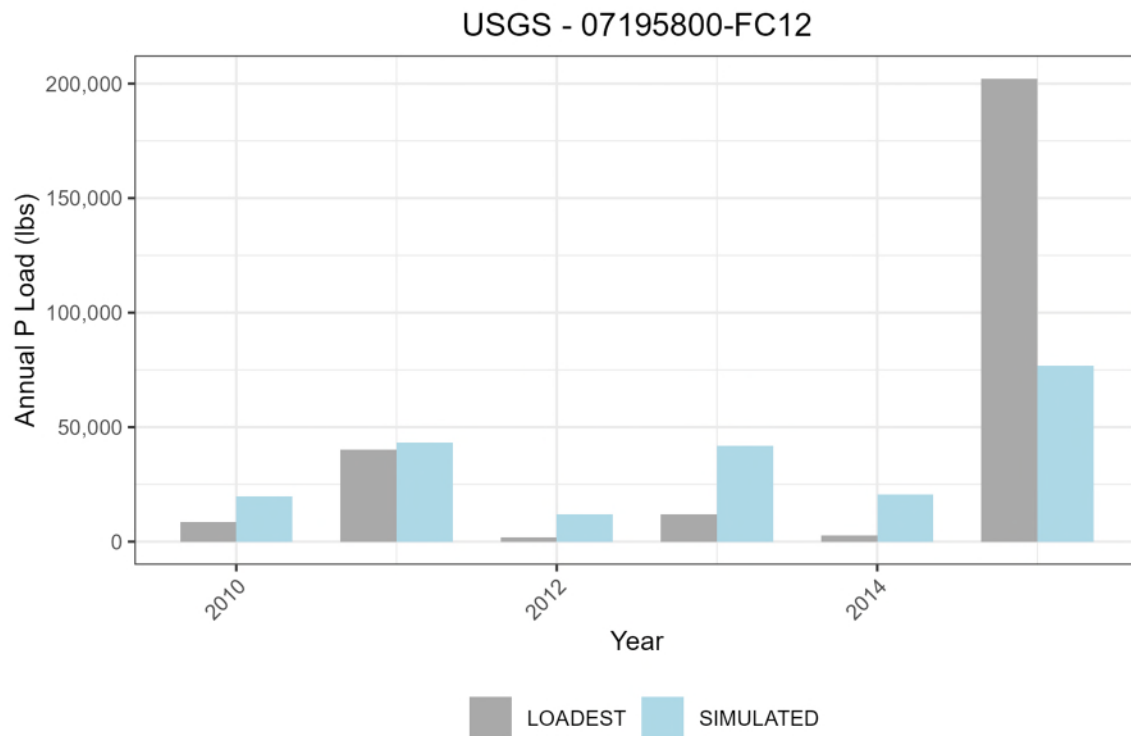


Figure 3. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07195000--AWRC FC12 and Subbasin 16.

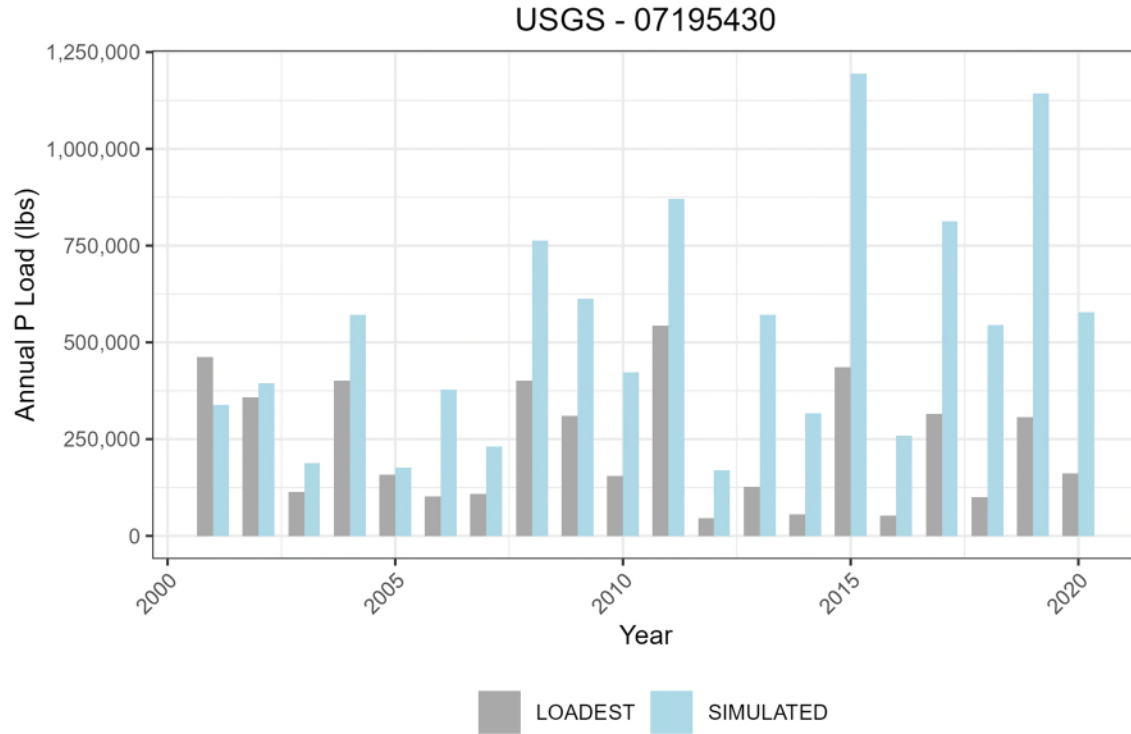


Figure 4. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07195430 and Subbasin 25.

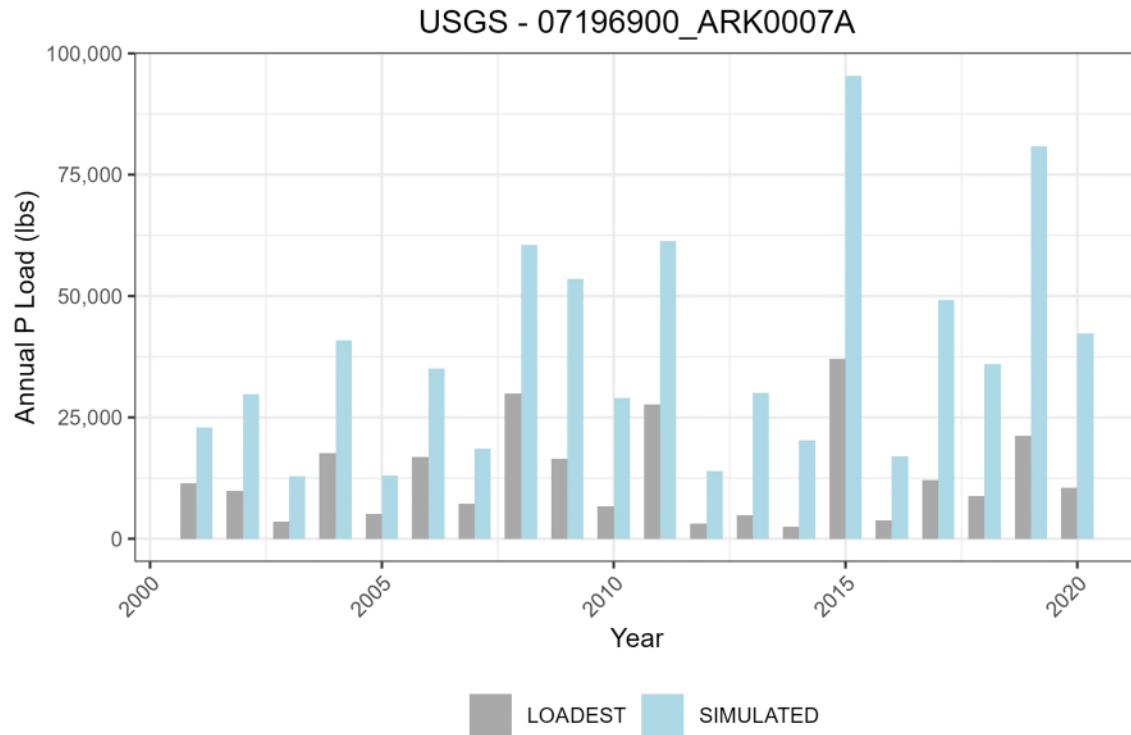


Figure 5. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07196900--AR-DEQ ARK0007A and Subbasin 27.

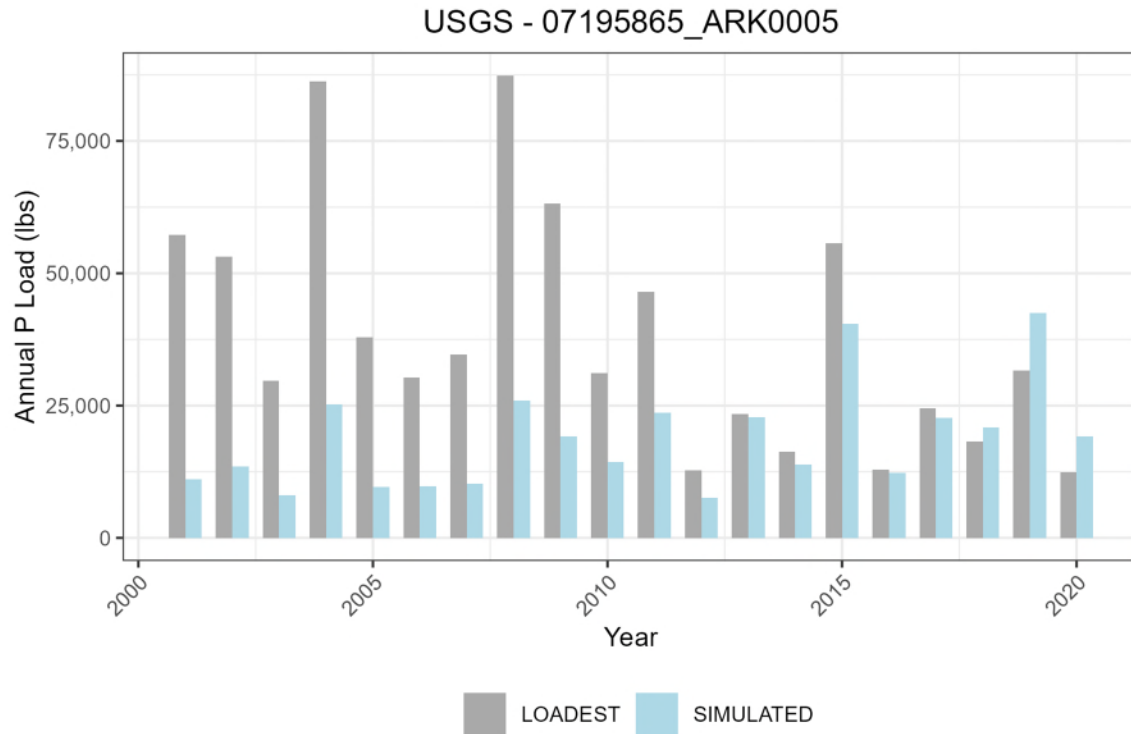


Figure 6. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07195865--AR-DEQ ARK0005 and Subbasin 17.

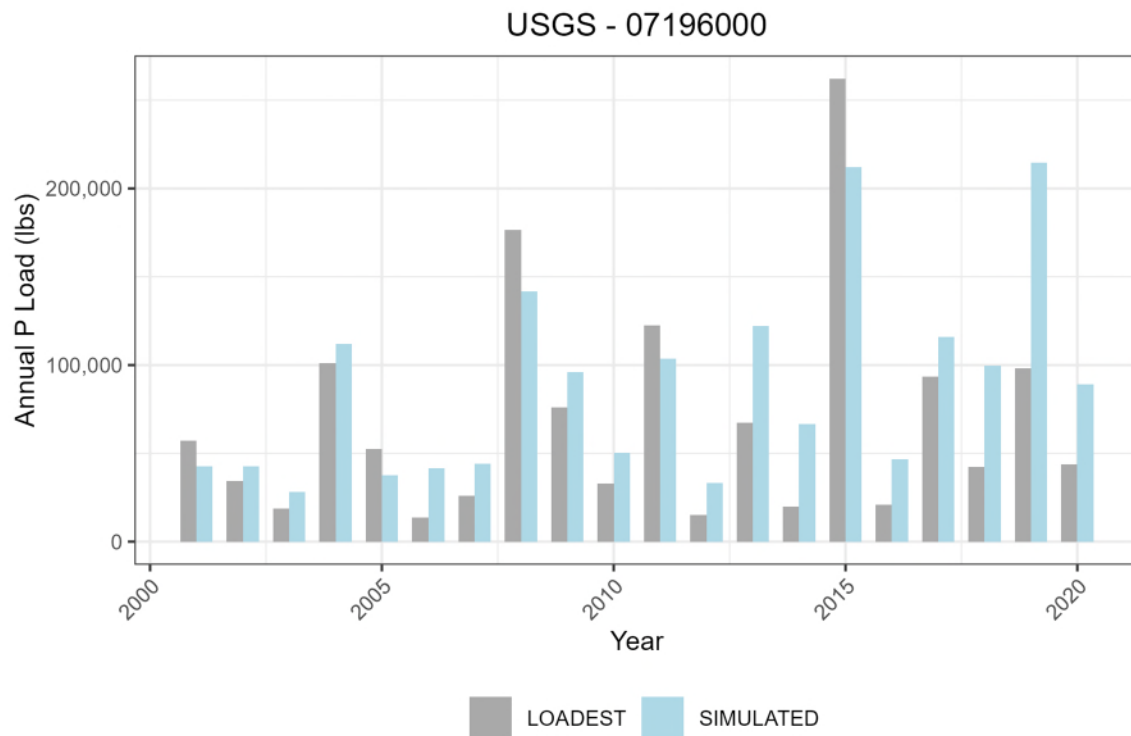


Figure 7. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07196000 and Subbasin 19.

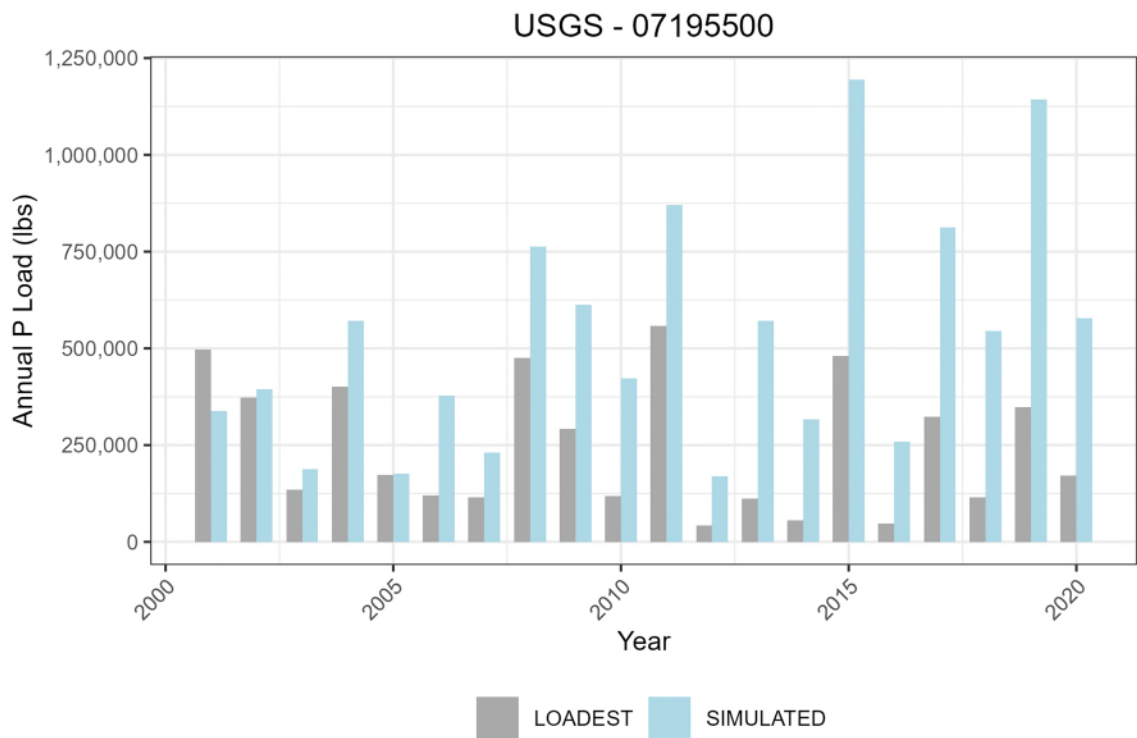


Figure 8. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for UGSG gage 07195500 and Subbasin 25.

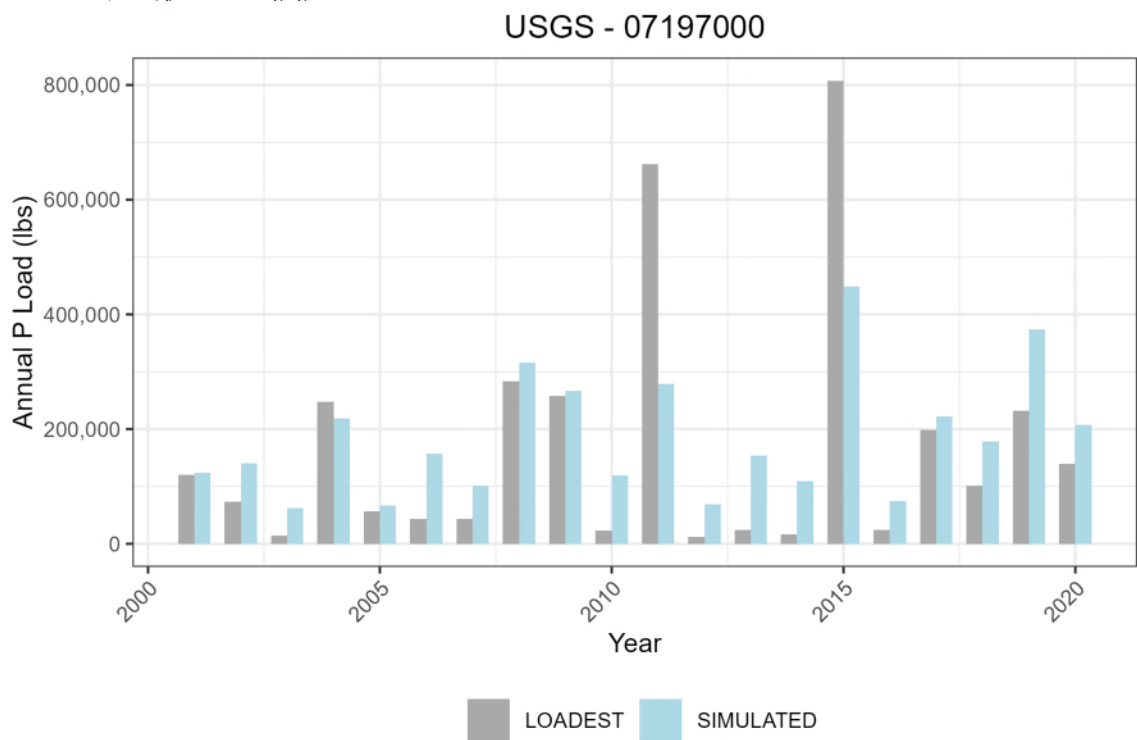


Figure 9. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for UGSG gage 07197000 and Subbasin 35.

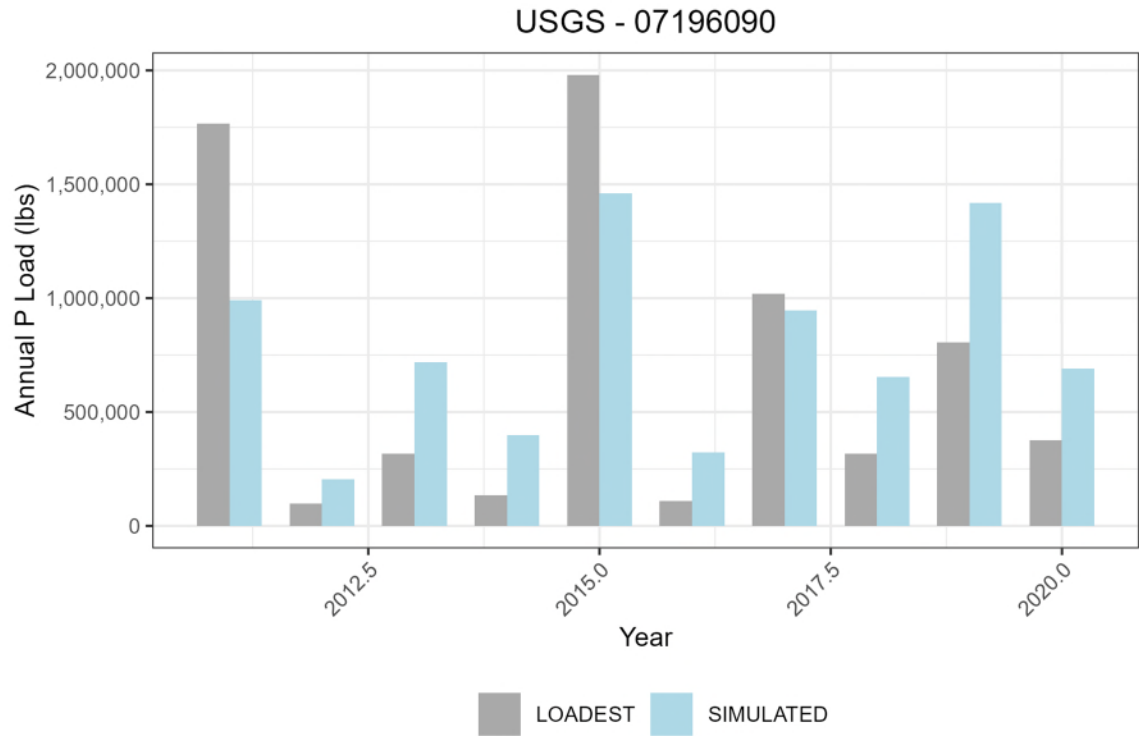


Figure 10. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for UGSG gage 07196090 and Subbasin 37.

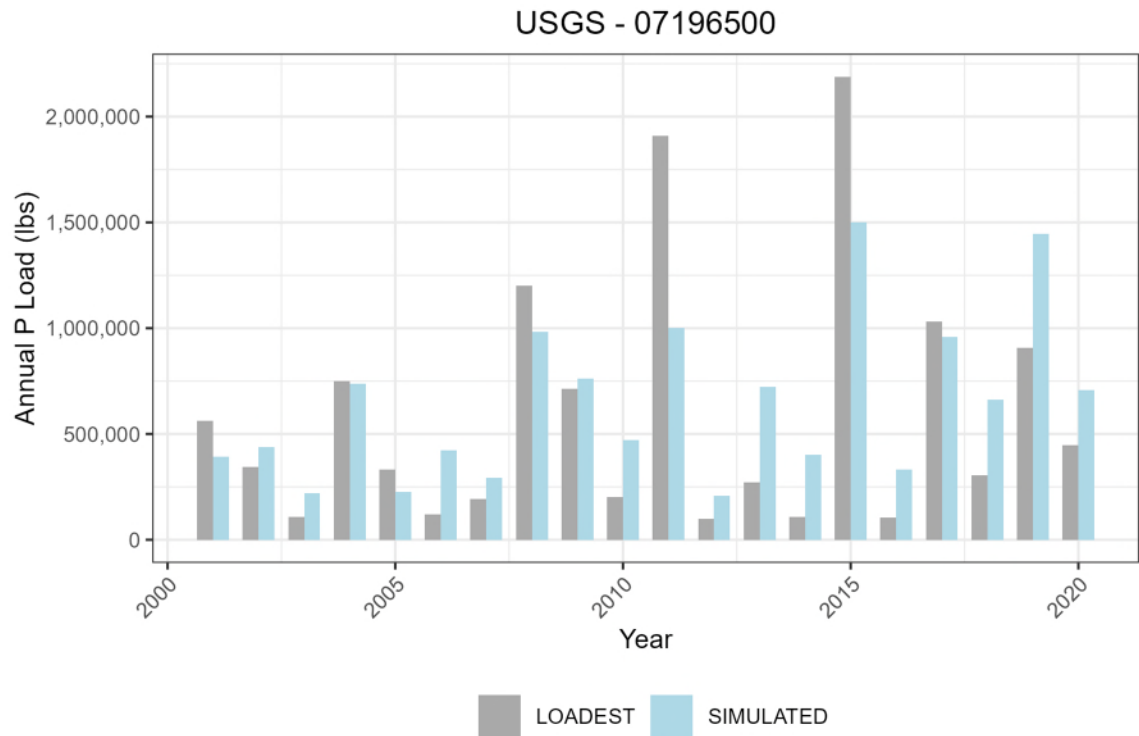


Figure 11. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for UGSG gage 07196500 and Subbasin 39.

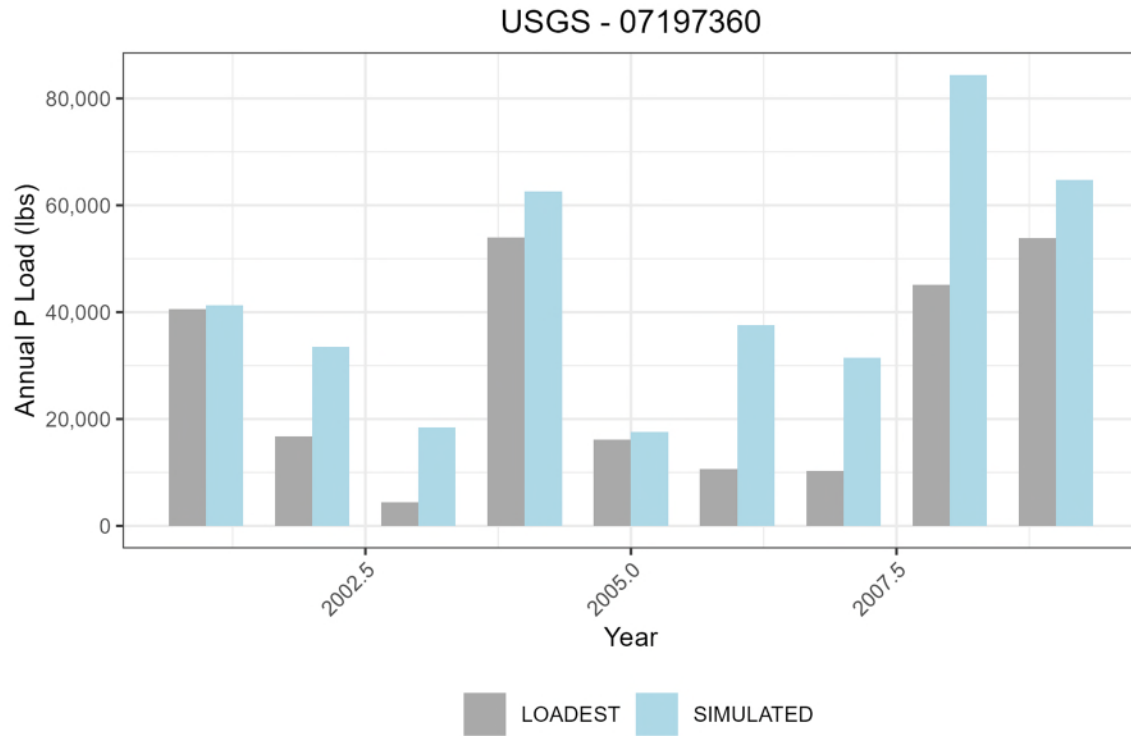


Figure 12. Comparison of annually averaged total phosphorus from LOADEST timeseries using observed values (grey) and SWAT simulation (blue) for USGS gage 07197360 and Subbasin 43.

RELiance MATERIALS

- Abbaspour, K. C., Vejdani, M., & Haghighat, S. (2007). *SWAT-CUP Calibration and Uncertainty Programs for SWAT*.
- Arnold, J., Kiniry, J., Srinivasan, R., Williams, J., Haney, E., Neitsch, S., 2013. SWAT 2012 input/output documentation. Texas Water Resources Institute.
- Arsenault, R., Brissette, F., Martel, J.-L., 2018. The hazards of split-sample validation in hydrological model calibration. *Journal of hydrology* 566, 346-362.
- Donigian, J. A. (2002). Watershed Model Calibration and Validation: The HSPF Experience. *Proceedings of the Water Environment Federation*, 2002, 44-73. doi:10.2175/193864702785071796
- SR Ghimire, AC Nayak, J Corona, R Parmar, R Srinivasan, K Mendoza, J Johnston. 2022. *Holistic Sustainability Assessment of Riparian Buffer Designs: Evaluation of Alternative Buffer Policy Scenarios Integrating Stream Water Quality and Costs*. *Sustainability* 14 (19), 12278.
- SR Ghimire, J Corona, R Parmar, G Mahadwar, R Srinivasan, K Mendoza, J Johnston. 2021. *Sensitivity of Riparian Buffer Designs to Climate Change—Nutrient and Sediment Loading to Streams: A Case Study in the Albemarle-Pamlico River Basins (USA) Using HAWQS*. *Sustainability* 13 (22), 12380.
- Hamberg L, Malmivaara-Lämsä M, Lehtvähä S, O'Hara RB, Kotze DJ. 2010. *Quantifying the effects of trampling and habitat edges on forest understory vegetation—a field experiment*. *J. Environ. Manag.* 91:1811–20.
- Harmel, R.D., R.J. Cooper, R.M. Slade, R.L. Haney, and J.G. Arnold. 2006. Cumulative uncertainty in measured streamflow and water quality data for small watersheds. *Trans. ASABE* 49(3): 689-701.
- Harmel, D. R., & Smith, P. K. (2007). Consideration of measurement uncertainty in the evaluation of goodness-of-fit in hydrologic and water quality modeling. *J. Hydrol.*, 337(3), 326- 336. <http://dx.doi.org/10.1016/j.jhydrol.2007.01.043>.
- HAWQS. (2023). *HAWQS System 2.0 and Data to model the lower 48 conterminous U.S using the SWAT model Version V2* [dataset]. Texas Data Repository. <https://doi.org/10.18738/T8/GDOPBA>
- Mittelstet, Aaron R.; Storm, Daniel E.; and White, Michael J., (2016) Using SWAT to enhance watershed-based plans to meet numeric water quality standards. *Biological Systems Engineering: Papers and Publications*. 386.
- Moriasi, D., Arnold, J., Van Liew, M., Bingner, R., Harmel, R. D., & Veith, T. (2007). Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. *Transactions of the ASABE*, 50. doi:10.13031/2013.23153
- Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2011. Soil and water assessment tool theoretical documentation version 2009. Texas Water Resources Institute.
- Patil, S. D., & Stieglitz, M. (2015). Comparing spatial and temporal transferability of hydrological model parameters. *Journal of Hydrology*, 53(6), 1355-1367. doi:10.1111/1752-1688.12594

Poméon, T., Diekkrüger, B., Springer, A., Kusche, J., & Eicker, A. (2018). Multi-Objective Validation of SWAT for Sparsely-Gauged West African River Basins—A Remote Sensing Approach. *Water*, 10(4), 451.

Shen, H., Tolson, B.A., Mai, J., 2022. Time to Update the Split-Sample Approach in Hydrological Model Calibration. *Water Resources Research* 58, e2021WR031523.

Illinois River Basin SWAT model with 4 scenarios - Database (served via USB drive to Defendants on 11/18/2024)

OCC IRW Poultry Farm Geo-spatial Map- KMZ Database (served via sharefile on 11/18/24)

"Environmental analysis and evaluation using HAWQS" Ecosystem Processes Division Landscape and Aquatic Systems Modeling Branch Quality Assurance Project Plan US EPA, Office of Research and Development, Center for Environmental Measurement and Modeling, (Jan. 22, 2024); Contract No: 68HE0C18D0001

"Environmental analysis and evaluation using HAWQS" Ecosystem Processes Division Landscape and Aquatic Systems Modeling Branch Quality Assurance Project Plan US EPA, Office of Research and Development, Center for Environmental Measurement and Modeling (February 17, 2022)

Sensitivity of Riparian Buffer Designs on Nutrients and Sediment Loadins into the Watershed Scale Streams" Ecosystem Processes Division Landscape and Aquatic Systems Modeling Branch Quality Assurance Project Plan US EPA, Office of Research and Development, Center for Environmental Measurement and Modeling (Dec. 18, 2020)

Programmatic Quality Assurance Project Plan (P-QAPP) for Economic, Environmental, and Regulatory Analytical and Evaluation Support for Clean Water Regulations, Ver. 2, Office of Water Programs (June 27, 2023)

Hydrologic and Water Quality System (HAWQS), Quality Assurance Product Plan, US EPA Office of Water (April 1, 2014): Texas A&M AgriLife Research Contract with USEPA re: HAWQS: *Contract No: C_DOCCM130105CT0027 EP-G11H-00057*

August 25-29, 2023 correspondence from Katie Mendoza to Brad Rogers and Shannon Phillips re: Cattle Stocking Rate

Federal Register, USEPA, Waters of the United States Rulemaking (2023), publicly available at: <https://www.federalregister.gov/documents/2023/01/18/2022-28595/revised-definition-of-waters-of-the-united-states>

USEPAm Meat and Poultry Products Effluent Guidelines (2024), publicly available at: <https://www.epa.gov/eg/meat-and-poultry-products-effluent-guidelines#current-rulemaking>

August 22, 2023 – October 10, 2023 correspondence from Shannon Phillips to Katie Mendoza, Brad Rogers and Raghavan Srinivasan re: Poultry Facilities in Illinois River.

PRISM Climate Data (1981-2020); publicly available at: <https://prism.oregonstate.edu/>

USDA National Resrouces Conservation Service Soil Survey Geographic Database (2018); publicly available at: <https://www.nrcs.usda.gov/resources/data-and-reports/soil-survey-geographic-database-ssurgo>

USDA NRCS State Soil Geographic (STATSGO) Database (2018), publicly available at: https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/geo/?cid=nrcs142p2_053629

National Land Cover Database (NLCD) (2016), publicly available at: <https://www.mrlc.gov/data>

USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) (2014-2017), publicly available at https://www.nass.usda.gov/Research_and_Science/Cropland/Release/

USDA NASS Fields (2006-2010), publicly available at: <https://lcluc.umd.edu/metadata/conterminous-united-states-conus-field-extraction>

U.S. Fish and Wildlife Service (FWS) National Wetlands Inventory (NWI) (2006-2010), publicly available at: <https://www.fws.gov/program/national-wetlands-inventory>

National Atmospheric Deposition Program (NADP) data (1980-2020), publicly available at: <https://nadp.slh.wisc.edu/>

Watershed boundaries (2019), publicly available at: https://www.usgs.gov/national-hydrography/national-hydrography-dataset?qt-science_support_page_related_con=0#qt-science_support_page_related_con

Stream Network data (2019), publicly available at: https://www.usgs.gov/national-hydrography/national-hydrography-dataset?qt-science_support_page_related_con=0#qt-science_support_page_related_con

USGS National Elevation Dataset (NED) (2018), publicly available at: <https://gdg.sc.egov.usda.gov/Catalog/ProductDescription/NED.html>

Point Sources, EPA Hypoxia Task Force (HTF) (2019), publicly available at: <https://echo.epa.gov/trends/loading-tool/hypoxia-task-force-nutrient-model>

EPA Integrated Compliance Information System National Pollutant Discharge Elimination System (ICIS-NPDES) (2019), publicly available at: <https://echo.epa.gov/tools/data-downloads/icis-npdes-download-summary>

USDA NRCS crop management zone data (2010), publicly available at: <https://onlinelibrary.wiley.com/doi/10.1111/1752-1688.12384>

U.S. Army Corps of Engineers (USACE) National Inventory of Dams (NID) (2018), publicly available at: <https://nid.sec.usace.army.mil/#/>

Ponds, Potholes, and Reservoirs data (2019), publicly available at: https://www.usgs.gov/national-hydrography/national-hydrography-dataset?qt-science_support_page_related_con=0#qt-science_support_page_related_con

Crop data (2014-2017), publicly available at: https://www.nass.usda.gov/Research_and_Science/Cropland/Release/

Wetlands data (2018), publicly available at: <https://www.fws.gov/program/national-wetlands-inventory>

Water Use Data (2015), publicly available at: <https://www.usgs.gov/mission-areas/water-resources/science/water-use-united-states>

SWAT model used on HAWQS platform rev688, publicly available at:
<https://swat.tamu.edu/software/swat/previous/>; <https://swat.tamu.edu/>

HAWQS 2.0: Hydrologic and Water Quality System Ver. 2 Technical documentation (2023), publicly available: https://hawqs.tamu.edu/content/docs/HAWQS_2.0_Technical_Documentation.pdf

USA Natural Resources Conservation Service Small Watershed Program PL556, publicly available at: <https://www.nrcs.usda.gov/conservation-basics/conservation-by-state/north-dakota/small-watershed-program-pl556>

USDA Poultry Production and Value (2021), publicly available at:
https://www.thepoultryfederation.com/images/2021_Poultry-Production__Value.pdf

The Poultry Federation Facts & Figures, publicly available at:
<https://www.thepoultryfederation.com/resources/facts-figures>

Purdue University, Lai, et al, Calculation of Poultry Manure production in Indiana, publicly available at: <https://engineering.purdue.edu/adt/PoultryManure/PurduePoultryDayPoster8-28-12.pdf>

Redfearn, D., Bidwell, T., Stocking Rate: The Key to Successful Livestock Production (Feb. 2017); publicly available at: <https://extension.okstate.edu/fact-sheets/stocking-rate-the-key-to-successful-livestock-production.html>

Range_class_methods_Appenix A: Development of Current Digital Land Use Data Using 30 m TM (Landsat 5) Imagery for the Illinois River.

USDA Census Data for Oklahoma (2017), publicly available at:
https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/County_Profiles/Oklahoma/index.php

USDA Census Data for Arkansas (2017), publicly available at:
https://www.nass.usda.gov/Publications/AgCensus/2017/Online_Resources/County_Profiles/Arkansas/index.php

<https://pubs.er.usgs.gov/publication/sir20065286>

Oklahoma Department of Environmental Quality (ODEQ) 2022 Appendix C- 303(d) List of Impaired Waters, publicly available at: https://www.deq.ok.gov/wp-content/uploads/water-division/OK_2022-Appendix-C-Final.pdf

Arkansas Department of Environmental Quality (ADEQ) 2022 303(d) Impaired Waters List, publicly available at: <https://www.adeq.state.ar.us/water/planning/integrated/303d/pdfs/2022/2022-draft-impaired-waters.pdf>

2022 303d Listed Waterways graphic, *created with* ADEQ 2022 303(d) list, ODEQ 2022 303(d) list.

LOADEST Input data 2000-2020- (served via sharefile on 11-18-2024).

Illinois River Basin SWAT model with 6 scenarios and observation data - (served via USB drive to Defendants on 11/18/2024)

Katherin (Kullgren) Mendoza
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Work Experience:

RESEARCH SPECIALIST III

Texas A&M AgriLife Research- Blackland Research Extension Center
720 E Blackland Road (REMOTE)
Temple, TX

11/2020 - Present

Supervisor: Raghavan Srinivasan (979-777-9822)

Texas A&M AgriLife Research, Blackland Research Extension Center (BREC) develops new technologies and management strategies to improve water, soil, and other natural resources. The Soil and Water Assessment Tool (SWAT) is deployed world-wide to increase agricultural production, water supply, and the sustainability of land.

COMPREHENSIVE HYDROLOGIC ANALYSIS: Adapt mathematical and statistical models for evaluation, identification, collection, and analysis of data used to support surface and ground water hydrologic projects. Modify and run statistical coding using PYTHON and R and proficient with Microsoft Access. Apply statistical analysis to review and analyze water resources determining the usefulness of data and the statistical significance of the output from the model and how it can be applied and quantified. Conduct comprehensive statistical quality assessment and quality assurance of all input and output data. Use the United States Geological Survey (USGS) Load Estimator (LOADEST) statistical tool to estimate water quality loadings in a stream from data sampling which identifies sampling errors and tests for significance to provide a statistically sound time series to use for calibration of the model and other water quality testing.

COMPLEX STATISTICAL ANALYSIS: Applied complex statistical techniques and automated the calibration and validation of the SWAT model for the Environmental Protection Agency Office of Water (EPA-OW) and the EPA Office of Research and Development (EPA-ORD). Review the sources of data and reliability of the statistics proposed to generate outputs and outcomes and cleanse all data collected using quality control processing algorithms and assess validity and reliability. As a migration to data driven initiatives, the model output is evaluated and translated into analytical reports used for guidance to the EPA and other state and local stakeholders to formulate operations decisions for compliance to the EPA water quality regulations in waterbodies and rivers.

RESEARCH & DEVELOPMENT: Plan, coordinate, and execute data modeling techniques and procedures including data processing algorithms. The output from the calibrated SWAT model is used by local, state, and federal agencies to advise and create policy on water use and quality. Improve the model by incorporating robust and finer resolution data as requested. Additionally, provide technical support to educational institutions to examine and evaluate the model output for research in water use and quality.

COORDINATION AND COLLABORATION: Implement annual strategic planning meetings to understand company trends and workflow, and to develop new approaches to best utilize resources to streamline productivity and solve any issues identified. Expedite workflow by coordinating internal staff to utilize resources efficiently and produce work products timely. Act as a liaison with external clients such as EPA, United States Core of Engineers (USACE), and university department heads to develop and plan project methodology for upcoming projects. Coordinate meetings with internal and external stakeholders to provide accurate and thorough updates on the status of current projects.

PRESENTATIONS & REPRESENTATION: Create technical documentation and reports for projects summarizing findings based on the analysis and interpretation of data and implement data repositories. Prepare and present presentations for senior leadership and at both national and international conferences. Develop and deliver group training materials for students and professionals both in-person and virtually. Co-author of three multidisciplinary peer-reviewed publications.

RESEARCH ASSOCIATE

The Center for Research on the Changing Earth System
(REMOTE)

Baltimore, MD

7/2006 - 8/2007; 8/2008 - 12/2021

Supervisor: Vikram Mehta (410-446-2684)

The Center for Research on the Changing Earth System (CRCES) develops water and food security options for the world to adapt to natural decadal climate cycles.

DATA FLUENCY: Wrote computer-assisted statistical operations and designed complex statistical analysis using FORTRAN, GrADS, and IDL software. Audited the procedures for quality assessment and quality control to verify accuracy and validity.

MATHEMATICAL REASONING: Identified impacts of decadal climate variability on water resources and agriculture in the Missouri and Mississippi River Basins, using statistical analysis of hydro-meteorological, river flow, crop yield and production, and water-borne commerce data and impact models such as EPIC and SWAT. This was done by collecting, computing, and analyzing statistical data, looking for central tendency and skewness of the data. Both simple and multi-variate correlation was computed along with the analysis of variance and significance testing.

STATISTICAL THEORY AND MODELS: Analyzed oceanic and atmospheric conditions for local, regional, and global droughts and floods in agricultural and water resource / transportation sectors. Forecasted precipitation and streamflow for the United States Core of Engineers (USACE) to advise on dredging requirements for barge transportation on waterways across the US. Executed statistical analysis and quality control of large ocean and atmosphere data sets to identify variability patterns and determine their underlying causes.

FORECASTING: Used the results from principal component analysis, multi-linear regression analysis, Monte Carlo simulation, correlation, and multiple correlation to find the spatial and temporal relationship of decadal sea surface temperatures to precipitation and temperature to forecast wet and dry periods across the globe at time steps ranging from one season to five years.

PUBLICATIONS: Assembled literature reviews and research for projects and books, ensuring compliance with copyright and other requirements of scientific journals and book publishers. Co-authored eight peer-reviewed publications where I designed, created, and implemented all the statistical analysis. Spearheaded the data gathering, quality assessment, analysis, and data visualization, and was the sole internal editor for two published books. Published forecasting results and other project outcomes on company website.

ASSISTANT DIRECTOR OF RESEARCH

Florida Center for Reading Research

2010 Levy Ave

Tallahassee, FL

8/2007 - 8/2008

Supervisor: Yaacov Petscher (850-644-9352)

COMPUTER-ASSISTED STATISTICAL OPERATIONS: Analyzed student assessment data through statistical software packages such as SAS and SPSS, using logistic regression and multivariate models.

TECHNICAL ADVISOR: Managed, supported, and analyzed student assessment data using ACCESS-SQL for the Florida Assessment Project, a reading assessment tool licensed to the Florida Department of Education.

SUPERVISE AND COLLABORATE: Supervised personnel in data analysis, offering guidance to maximize quality control and time management and ensure prioritization of tasks to achieve critical deadlines. Collaborated with department heads to develop the plan and methodology for projects. Coordinated department presentations on an array of educational research tools, techniques, and results.

CO-AUTHOR: Compiled one peer-reviewed publication using statistical test of significance in the skewness and kurtosis of the distribution of the Dynamic Indicators of Basic Early Literacy Skills (DIBELS) measures, quantile regression, area under the curve, and sensitivity for false positives and positive prediction power resulting in the measures initially characterized by strong floor effects. This lessened across administrations and eventually all measures except one moved toward central tendency and showed near normal distribution. The floor effect impacted the ability of these measures to predict future reading outcomes.

Education:

Florida State University Tallahassee, FL United States
Master's degree 5/2006 **GPA:** 3.63/4.0
Major: Meteorology **Minor:** Math & Physics

Florida State University Tallahassee, FL United States
Bachelor's degree 5/2004 **GPA:** 3.31/4.0
Major: Meteorology **Minor:** Math & Physics

Professional Publications:

BOOKS: [Collected data, conducted analysis and visualization, and was internal editor.]

Mehta, V.M. Natural Decadal Climate Variability: Phenomena, Mechanisms, and Predictability; CRC Press (Taylor & Francis): Boca Raton, 374 pages, 2020.

Mehta, V.M. Natural Decadal Climate Variability: Societal Impacts; CRC Press (Taylor & Francis): Boca Raton, 325 pages, 2017.

PEER-REVIEW PUBLICATIONS:

A Bawa, **K Mendoza**, R Srinivasan, R Parmar, D Smith, K Wolfe, J Johnston, J Corona. 2024. Calibration using R-programming and parallel processing at the HUC12 subbasin scale in the Mid-Atlantic region: Development of national SWAT hydrologic calibration. Environmental Modelling & Software 176, 106019.

SR Ghimire, AC Nayak, J Corona, R Parmar, R Srinivasan, **K Mendoza**, J Johnston. 2022. Holistic Sustainability Assessment of Riparian Buffer Designs: Evaluation of Alternative Buffer Policy Scenarios Integrating Stream Water Quality and Costs. Sustainability 14 (19), 12278.

SR Ghimire, J Corona, R Parmar, G Mahadwar, R Srinivasan, **K Mendoza**, J Johnston. 2021. Sensitivity of Riparian Buffer Designs to Climate Change—Nutrient and Sediment Loading to Streams: A Case

Study in the Albemarle-Pamlico River Basins (USA) Using HAWQS. Sustainability 13 (22), 12380.

VM Mehta, **K Mendoza**, NJ Rosenberg, R Srinivasan. 2021. High-resolution simulations of decadal climate variability impacts on spring and winter wheat yields in the Missouri River Basin with the Soil and Water Assessment Tool (SWAT). Climatic Change 168, 1-19.

Mehta V.M., Wang, H, **Mendoza, K.** 2019: Predictability of phases and magnitudes of natural decadal climate variability phenomena in CMIP5 experiments with the UKMO-HadCM3, GFDL-CM2.1, NCAR-CCSM4, and MIROC5 global earth system models. Clim. Dyn., 52, 3255-3275.

Mehta, V.M., Wang, H., **Mendoza, K.**, 2018: Simulation of Three Natural Decadal Climate Variability Phenomena in CMIP5 Experiments with the UKMO-HadCM3, GFDL-CM2.1, NCAR-CCSM4, and MIROC5 Global Earth System Models. Clim. Dyn, 51, 1559-1584.

Mehta, V.M.; **Mendoza, K.**; Daggupati, P.; Srinivasan, R.; Rosenberg, N.J.; Deb, D. 2016: High-Resolution Simulations of Decadal Climate Variability Impacts on Water Yield in the Missouri River Basin with the Soil and Water Assessment Tool (SWAT). J. Hydrometeorol. 17, 2455-2476, doi: 10.1175/JHM-D-15-0039.1.

Mehta, V.M.; Wang, H.; **Mendoza, K.**; Rosenberg, N.J., 2014: Predictability and Prediction of Decadal Hydrologic Cycles: A Case Study in Southern Africa. Weather Clim Extrem., 3, 47-53, doi: 10.1016/j.wace.2014.04.002.

Mehta, V.M.; Wang, H.; **Mendoza, K.**, 2013: Decadal predictability of tropical basin-average and global-average sea-surface temperatures in CMIP5 experiments with the HadCM3, GFDL-CM2.1, NCAR-CCSM4, and MIROC5 global earth system models. Geophys. Res. Lett., 40, 2807-2812. doi:10.1002/grl.50236.

Mehta, V.M.; Rosenberg, N.J.; **Mendoza, K.**, 2012: Simulated Impacts of Three Decadal Climate Variability Phenomena on Dryland Corn and Wheat Yields in the Missouri River Basin. Agr. Forest. Meteorol. 152, 109-124, doi: 10.1016/j.agrformet.2011.09.011.

Mehta, V.M.; Rosenberg, N.J.; **Mendoza, K.**, 2011: Simulated Impacts of Three Decadal Climate Variability Phenomena on Water Yields in the Missouri River Basin. J. Am. Water Resour. Assoc. 47, 126-135, doi: 10.1111/j.1752-1688.2010.00496.x.

HW Catts, Y Petscher, C Schatschneider, M Sittner Bridges, **K Mendoza**. 2009 Floor effects associated with universal screening and their impact on the early identification of reading disabilities. Journal of learning disabilities. 42 (2), 163-176.

Kim, K.-Y.; **Kullgren, K.R.**; Lim, G.-H.; Boo, K.-O.; Kim, B.-M. Physical Mechanisms of the Australian Summer Monsoon: Part II: Variability of Strength and Onset and Termination Times. J. Geophys. Res. 2006, 111, D20105, doi: 10.1029/2005JD006808.

Kullgren, K.R.; Kim, K.-Y. 2006: Physical Mechanisms of the Australian Summer Monsoon: Part I: The Seasonal Cycle. J. Geophys. Res., 111, D20104, doi: 10.1029/2005JD006807.